REVERSE LOGISTICS, PROCESS INNOVATION, OPERATIONAL PERFORMANCE AND COMPETITIVE ADVANTAGE OF MANUFACTURING FIRMS IN KENYA

BY:

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DECLARATION

I, the undersigned, do declare that this research thesis is my original work and has not been submitted for any award to any other university, institution or college for examination other than the University of Nairobi.

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This doctoral thesis is dedicated to the Late Prof. Isaac Albert Wamola for his inspiration and for being a pillar of strength in my academic life; and to my children Andrew Mwanyota Lewela and Adrian Mwakio Lewela.

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ABBREVIATIONS AND ACRONYMS

AGFI	-	Adjusted Goodness of Fit Index
AMOS	-	Analysis of Moment Structures
AVE	-	Average Variance Extraction
CV	-	Coefficient of Variation
CFA	-	Confirmatory Factor Analysis
CFI	-	Comparative Fit Index
CLF	-	Common Latent Factor
CMIN/DF	-	Chi-Square/Degrees of Freedom
EMA	-	Energy Management Award
EMCA	-	Environmental Management and Co-ordination Act
GDP	-	Gross Domestic Product
GFI	-	Goodness of Fit Index
K-GESIP	-	Kenya Green Economy Strategy and Implementation Plan
KAM	-	Kenya Association of Manufacturers
KMO	-	Kaiser-Meyer-Olkin
KNBS	-	Kenya National Bureau of Statistics
MNCs	-	Multi National Corporations
MSV	-	Maximum Shared Variance
NEMA	-	National Environmental Management Authority
NFI	-	Normed Fit Index
PCA	-	Principal Component Analysis
RMSEA	-	Root Mean Square Error of Approximation
SD	-	Standard Deviation
SEM	-	Structural Equation Modeling
TLI	-	Turker Lewis Index
UN	-	United Nations
UNEP	-	United Nations Environment Programme
USA	-	United States of America
VIF	-	Variance Inflation Factor

ABSTRACT

Today globally, countries and manufacturing entities alike are concerned with environmental sustainability. Execution of reverse logistics strategies has been contemplated as a feasible alternative to mitigate the negative environmental effects of manufacturing. However the question has been whether implementing reverse logistics creates competitive advantage for manufacturing entities. Literature has also suggested that process innovations result in improved operational performance in the achievement of competitiveness. Specifically, the study objectives were to establish the influence of reverse logistics on competitive advantage; determine the influence of operational performance on the relationship between reverse logistics and a firm's competitive advantage; determine the influence of process innovation on the relationship linking reverse logistics and gaining internal operational proficiency; examine the conditional indirect effect on the relationship among reverse logistics, process innovation and operational performance on a firm's competitive advantage; and examine the joint effect of reverse logistics, process innovation and operational performance on a firm's competitive advantage. Appropriate hypotheses were developed from the specific objectives respectively. Using a positivist philosophy and correlation cross-sectional survey design, primary data were collected among 340 KAM registered manufacturing firms in Kenya using a structured questionnaire. A response rate of 44.4 percent was attained. In data analysis, Covariance-based, SEM was used. Results from the hypotheses tests revealed a statistically significant influence of reverse logistics on a firm's competitive advantage. Secondly, operational performance significantly mediated the association linking reverse logistics and a firm's competitive advantage. Third, the relationship linking reverse logistics and gaining internal operational competency was not significantly moderated by process innovation. Fourth, process innovation and the operational performance had a partial moderated-mediation influence on the association linking reverse logistics and competitive advantage. Finally only operational performance had a significant and positive influence in the joint model. The study thus confirmed that implementation of reverse logistics strategies will lead firms to experience increased customer loyalty, increased market share, improved brand recognition and an increase in revenues. It further confirmed that when resources are mobilized uniquely, they create comparative advantage consequently leading to competitive advantage. The study recommended that manufacturing firms should implement reverse logistics as an integrated intervention consisting of outsourcing, collaborative enterprising, green strategies and closed-loop supply chain approaches to achieve organizational and environmental benefits. The study further recommended that implementation of reverse logistics should be guided by a process that requires identifying the uniqueness of resources the organization has and strategically placing these resources in a manner that builds comparative advantage. Policymakers within the manufacturing sector in Kenya should improve the regulatory framework to upscale application of reverse logistics strategies. The research identified replication of the study using direct measures for all the study variables and in other contexts as possible future research streams. Further making intra-industry or intra-sectoral comparisons would also be useful in generating knowledge on the implementation of reverse logistics.

CHAPTER ONE: INTRODUCTION

1.1 Background of the Study

Environmental concerns presently have led manufacturing firms to redesign their processes in order to have environmentally friendly manufacturing (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). As a result, manufacturers and consumers alike are required to dismantle used products into their constituent parts for reuse, recycling, or safe disposal (Sheth, Sethia & Srinivas, 2011). Reverse logistics is concerned with moving “end of useful life” goods from consumers to manufacturers so as to recapture value or ensure environmentally friendly disposal (Stock, 1992). In the process of strategically managing the product returns process, firms also aim at gaining operational efficiency (Stock, Speh & Shear, 2006). Similarly, the introduction of process innovation in managing reverse logistics helps firms to generate and implement strategies that result in efficient and effective business models (Barney, 1991). Gaining operational efficiency by strategically managing product returns can lead to improving a firm’s competitory position.

In this study, the theories that were used to explain why organizations implement reverse logistics programs and how these relate to process innovation, operational performance and competitive advantage include transaction cost theory, the resource advantage theory of competition, diffusion of innovation theory and institutional theory. Transaction cost theory establishes a framework for explaining the development of optimal organization structure and relationships among operational systems (Williamson, 1991). Resource advantage theory of competition recognizes that unique resources found in a firm can lead to innovative internal capabilities and hence competitive advantage (Hunt & Morgan, 2005). The diffusion of innovation theory creates a platform for explaining factors hindering or enabling the diffusion of innovations (Rogers, 2003). Finally, institutional theory which was the primary theory in the study was relevant in explaining the effects of institutional pressures on various study variables (North, 1991).

The manufacturing sector accounted for 10.3 percent of Kenya's Gross Domestic Product (GDP) in 2017 (Kenya National Bureau of Statistics (KNBS), 2017). As a consequence of environmental concerns and climate change effects, legislation requiring manufacturers to be environmentally conscious have been developed. Through the Environmental Management and Co-ordination Act (EMCA) No.8 of 1999, Kenya established the National Environmental Management Authority (NEMA) to be the government's arm mandated to implement policies concerning the environment. Similarly through the Kenya Green Economy Strategy and Implementation Plan (K-GESIP), Kenya is adopting various green economy approaches and policies (KNBS, 2017). Despite these, uptake of strategies to mitigate environmental effects among manufacturing firms has been slow with firms being more profit-oriented (World Bank, 2016).

1.1.1 Reverse Logistics

According to Stock (1992) reverse logistics entails logistics activities relating to recycling and disposal of waste and hazardous materials management. Reverse logistics as a process systematically involves the cost-effective planning, implementation, and control of the efficient movement of raw materials, partly completed and finished products, and the associated information from their usage locale back to their origin either to reclaim value or for apt disposal (Rogers & Tibben-Lembke, 1999). Environmental concerns, effects of climate change, scarcity of manufacturing raw materials and technological advancements have increased attention and focus on reverse logistics (Blumberg, 1999; Dias & Braga Jr., 2016). Factors leading to increased volumes of reverse product flow include; lowering of product quality; liberal returns polices; buyer's changing preferences; increased internet product purchases; and shortened product life cycles (Bernon & Cullen, 2007; Ravi & Shankar, 2015).

The strategies proposed to implement reverse logistics programs include outsourcing, collaborations, adopting green strategies or implementing reverse logistics from a product-life cycle approach using closed-loop supply strategy. Outsourcing enables a firm to concentrate on its core capabilities, achieve higher flexibility and transfer risk to a third party (He & Wang, 2005; Moghaddam, 2015; Hsu, Tan & Mohamad-Zailani, 2016). Collaborations led by industry associations or governments can integrate reverse logistics operations for firms in an industry (Hung-Lau & Wang, 2009). Adopting green strategies such as reuse, recycle and remanufacture help in "greening" the supply chain (Rogers & Tibben-Lembke, 2001; Rao & Holt, 2005). Finally, implementing reverse logistics using the product-life cycle approach allows for the recreation of value through the closed-loop supply chain (Closs, Speier & Meacham, 2011; Govindan et al., 2015; Sangwan, 2017).

1.1.2 Process Innovation

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 innovations. Schumpeter

(1934) identified innovations as of two types. The first is process innovation which consists of new production approaches and new sources of manufacturing inputs, semi-finished products or components. The second being product innovation which includes a new product, a new product quality, a new market, or a reconstitution of a new industry structure.

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 involve 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).

1.1.3 Operational Performance

Operational performance is the degree to which predetermined goals and targets are being accomplished using a process-oriented approach that measures' productivity of resources and the quality of outputs and outcomes of products and services (Shaw, 2003). Operational performance identifies and measures attributes that relate outcomes of firm processes to performance such as defect rates, production cycle time, and inventory turnover. Operational performance measurement is an on-going process of establishing, monitoring and pro-actively taking corrective action towards achieving organizational goals, efficiently and effectively (Carter, Kale & Grimm, 2000).

Various indices exist for measuring operational performance. Operational performance can be measured in terms of defect rate per item, the extent of customer complaints, degree of waste, mean- time failure rate, client query time, requisition lead time, throughput rate, and efficiency level (Slack, Chambers & Johnston, 2010). Studies have shown that the major operational performance dimensions include; cost, time/speed, operations flexibility, dependability and quality (Carter et al., 2000; Brah & Ying-Lim, 2006; De Souza & Brito, 2011; Chavez, Gimenez, Fynes, Wiengarten & Yu, 2013).

1.1.4 Competitive Advantage

Competitive advantage refers to the unique ability in a firm that enables it to have higher returns than its competitors (Kim & Hoskisson, 2015). To have competitive advantage firms need to offer distinct value propositions using customized value chains with unique trade-offs from those of its competitors (Porter, 2008). Building the product returns process to generate new market opportunities creates competitive advantage by attracting new clients and retaining existing ones (Jayaraman & Luo, 2007). Reverse logistics has facilitated the generation of competitive advantage through influencing the purchasing behavior of customers based on how the product returns are handled (Stock, Speh & Shear, 2006). Barney (1991) identified properties that permit the sustainable realization of competitive advantage to include resource value, the rarity of the resource, an imperfectly imitable resource, an imperfectly mobile resource and a non-substitutable resource.

Markley and Davis (2007) suggested customer loyalty, waste reduction, revenue increase, market share, and brand recognition as indices for measuring competitive advantage. Jayaraman and Luo (2007) similarly suggested customer relations, brand image and reputation as ways of assessing a firm's competitive advantage.

1.1.5 Manufacturing Sector in Kenya

The manufacturing field is a collection of firms all engaged in intermediate operations that transform substances, components or materials into new products using physical, chemical or mechanical processes. In spite of Kenya's position in East Africa as the most industrially developed country, the manufacturing field in Kenya is not dominant compared to the service and agricultural sectors (Kenya Association of Manufacturers (KAM), 2018). Growth in the manufacturing sector stood at 3.5 percent in 2016. The growth was occasioned by reduced energy costs. Overall, investments in the manufacturing sector stood at Kshs. 277.4 billion in 2016 with 300,900 persons in formal employment representing 11.8 percent of the formal jobs in the country (KNBS, 2017). Further the manufacturing sector contributed 11.8, 11.0, 10.7, 10.0 and 10.3 percent to GDP in the years 2012, 2013, 2014, 2015 and 2016 respectively. Appendix 2 shows the quantum index for manufacturing production from 2012 until 2016 with the year 2009 as the base year.

Although manufacturing firms globally are increasingly recognizing the importance of conserving the environment, implementation of strategies such as reverse logistics aimed at reducing environmental effect has been slow (KAM, 2018). This is because manufacturing firms in Kenya have information systems tailored to optimize forward logistics but similar systems for implementing reverse logistics have persisted at the planning stage. Similarly the development of asset value recovery systems is also at its infancy (Dekker, Fleischmann, Inderfurth & van Wassenhove, 2013). Reverse logistics requires additional infrastructure such as warehousing space, additional materials handling equipment and transportation vehicles, a factor which not many firms in Kenya are willing to invest in (Rogers, Banasiak, Brokman, Johnson & Tibben-Lembke, 2002). Further developing accurate demand forecasts for reverse logistics is more intricate compared to forecasting for forward logistics as a consequence of complexities of tracking defectives. Currently most manufacturing firms in Kenya tend to control product return processes at the individual business unit level and not as a supply chain. Finally the increasing volume of returns greatly exceeds the capacity of business units to manage reverse logistics effectively (Genchev, Glenn-Richey & Gabler, 2011).

1.2 Research Problem

A key assumption has been that reverse logistics strategies facilitate sustenance of future generations to fulfill their needs by holding present generations environmentally accountable to all shareholders including the number one shareholder, planet earth (Sheth et al, 2011; Dias & Braga Jr., 2016; Sangwan, 2017). Such strategies are opined to create innovative processes that ensure effective and efficient utilization of a firm's resources thereby legitimizing environmental effects on planet earth at a macro level and providing operational performance gains for firms at a micro-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).

Studies done in reverse logistics have been exploratory using case study research design (Jim & Cheng, 2006; Jayaraman & Luo, 2007; Hung-Lau & Wang, 2009; Genchev et al., 2011). More recently studies are using survey designs with regression modeling but with disparate results (Ho, Choy, Lam & Wong, 2012; Somuyiwa & Adebayo, 2014; Ravi & Shankar, 2015). These studies have also used varied sampling procedures with varying response rates (Ravi & Shankar, 2015; Hsu et al., 2016; Morgan et al., 2016). Further, there is a lack of the usage of more robust techniques to analyze the effect other extraneous variables have on the association between reverse logistics and performance (Huang & Yang, 2014; Govindan et al., 2015).

Manufacturing firms in Kenya in their quest to gain competitive advantage have not harnessed the potential of implementing reverse logistics programs. The main reason is that developing and implementing such a program has been considered to be a tedious process because of the complexities in developing demand forecasts for reverse logistics and capital requirements for additional infrastructure (Rogers et al., 2002). Similarly, a lack of information systems and asset recovery systems to support informed decision making while developing reverse logistics programs further complicates implementation (Dekker et al., 2013). The Kenyan manufacturing sector has also witnessed the exploitation of the weak institutional mechanisms for enforcing environmental legislation despite initiatives such as K-GESIP (World Bank, 2016). Only until recently have we seen research on reverse logistics in the African context (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.

Scholars have explored relationships among reverse logistics, process innovation, operational performance and competitive advantage and given disparate results. For instance, reverse logistics has the potential in achieving competitive advantage (Markley & Davis, 2007; Ravi & Shankar, 2015). However, studies in reverse logistics have mainly focused on adoption levels, implementation barriers or factors influencing adoption (Abdullah, Halim, Yaakub & Abdullah, 2011; Abdulrahman, Gunasekaran & Subramanian, 2014; Hosseini, Chileshe, Rameezdeen & Lehmann, 2014; Bouzon, Govindan & Rodriguez, 2018). These studies have not demonstrated how reverse logistics strategies impact a firm's competitive advantage. Hung-Lau and Wang (2009) opined that the independent effect of reverse logistics on competitive advantage has been hypothesized and tested with varied results.

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.

Studies have argued for an association linking reverse logistics and the generation of competitiveness advantageously without considering the effect of extraneous variables to this relationship (Stock, 2001; Jack et al., 2010; Huang & Yang, 2014). Further, although scholars have argued for a relationship between operational performance and competitive advantage Oral and Yolalan (1990), Voss, Åhlström and Blackmon (1997) and Carter et al. (2000) this was not from a reverse logistics perspective. Yet, reverse logistics practices have capacity to reduce clients' risk when purchasing products and add value to the customer (Russo & Cardinali, 2012). Rogers and Tibben-Lembke (2001) opined that reverse logistics programmes can assist a firm to minimize product returns by identifying problem areas and defect patterns through its value system. De Brito, Flapper and Dekker (2005) argued that such a value system has either direct (financial) or indirect (non-financial) benefits resulting in improved competitiveness of the firm. The above studies suggest reverse logistics and gaining competitiveness have a relationship contingent on process innovation and achieving operational competence. However the nature and strength of these relationships are unexplored. Similarly, the net effect of reverse logistics, process innovation and operational performance on competitive advantage is worthy of further investigation. This study sought to answer the following: What is the relationship among reverse logistics, process innovation, operational performance and competitive advantage of manufacturing firms in Kenya?

1.3 Research Objectives

The main objective of this study was to examine the relationships among reverse logistics, process innovation, operational performance and competitive advantage of manufacturing firms in Kenya. The specific objectives were:

i. To establish the influence of reverse logistics on competitive advantage.

ii. To determine the influence of operational performance on the relationship between reverse logistics and a firm's competitive advantage.

iii. To determine the influence of process innovation on the relationship between reverse logistics and operational performance.

iv. To examine the conditional indirect effect of process innovation and operational performance on the relationship between reverse logistics and a firm's competitive advantage.

v. To examine the joint effect of reverse logistics, process innovation and operational performance on a firm's competitive advantage.

1.4 Value of the Study

The proposed study is envisaged to make a contribution to knowledge, theory, policy-making and practice of reverse logistics. Theoretically the research findings will help academicians and firms to apprehend the significance of having a reverse logistics plan in manufacturing and the relative contributions of process innovation and operational performance on gaining competitive advantage. This will be achieved by providing an evidence-based framework that suggests the relationships underlying the research variables. Transaction cost theory, diffusion of innovations theory, institutional theory and the resource advantage theory of competition will be used to offer rational explanations to the relationship between reverse logistics, process innovation, operational performance and competitive advantage. This is useful to academicians as it helps in substantiating the theories.

Policymakers will gain an apprehension of issues in the application of reverse logistics approaches. Such understanding will influence the government and its departments to enact laws, develop policy guidelines or establish frameworks within which firms can implement reverse logistics. These will inform manufacturers of the strategic significance reverse logistics has to the economy of Kenya.

The study serves to apprise the application of reverse logistics approaches for manufacturing entities by providing a diagnostic tool for establishing weaknesses within current reverse logistics approaches. Study results could also be useful in prioritizing reverse logistics strategies application. The study further provides owners and managers of manufacturing firms with an opportunity to apprehend the position of reverse logistics as a key process for gaining competitiveness advantageously.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

This chapter discussed the theoretical and empirical evidence in understanding the relationships among reverse logistics, process innovation, operational performance and competitive advantage. A summary of the literature gap, proposed conceptual framework and hypotheses are provided.

2.2 Theoretical Foundations of the Study

This section introduced transaction cost theory, diffusion of innovation theory, resource advantage theory of competition and the institutional theory. Emphasis was in understanding conceptual, theoretical and methodological implications of these theories within the framework of this study.

2.2.1 Transaction Cost Theory

Transaction cost theory is guided by certain key premises. First, the basic unit of analysis for firms is a transaction and transaction cost optimizing behaviour is useful in studying firms (Williamson, 1991). Second, in optimizing transaction costs, the key is in balancing between transactions that have different attributes and governance structures with different costs and competences (Clemons & Row, 1992). Third, transaction costs are classified into coordination costs which are costs of decision making while integrating economic processes and transaction risk costs referring to the exposure of exploitation in the economic relationship (Geyskens, Steenkamp & Kumar, 2006). Fourth, the risk of opportunism exists in transactions. Opportunism refers to the disclosure of distorted or incomplete information with an aim to mislead, confuse or obscure others (Williamson, 1991). Fifth, the theory provides a framework for explaining why some operations are executed in-house whereas others are outsourced (Coase, 1937).

Transaction cost theory has limitations. First, although this theory has wide applicability, its functionality is not optimal because the theory is an evolutionary theory. Secondly, lack of integration across disciplines where the theory has been applied such as economics, law and operations has hindered its maturity and use (Geyskens et al., 2006).

Irrespective of this, transaction cost theory has relevance to this study. At the strategic level the theory provides a framework of how firm structure and operational systems can be established from a reverse logistics perspective. At a tactical level the theory guides in determining activities to be performed in-house and those to be outsourced and why. At the operational level, the theory provides guidance in the organization of the human asset such that internal governance structures, match team attributes (Williamson, 1991).

2.2.2 Resource Advantage Theory of Competition

The resource advantage theory of competition posits that organizations gain competitive advantage through marshaling comparative advantage internally (Hunt & Morgan, 2005). Accumulation of resources internal to the organization rather than the external environment should influence competitive strategy (Amit & Shoemaker, 1993). From the theory, the resource selection process determines how competition for comparative advantage is gained such that the organization is viewed as the transmissible unit of selection (Conner, 1991). Each organization has unique resources that become a comparative advantage source leading to advantageous opportunities in the market. Such resources provide long-term competitive advantage (Barney, 1991). The theory also recognizes innovation as endogenous to the organizational processes within a firm's competitive environment (Hunt & Madhavaram, 2012).

The limitations of this theory are first, the theory is only applicable to those economies that are not monopolistic but embrace competition (Hunt & Morgan, 2005). Secondly, resources of a firm are not always at a state of comparative advantage, therefore competitive advantage is not always assured (Barney, 1991). Finally, firms can determine their level of comparative advantage after competing in the market place not before.

Despite these, the theory becomes relevant in understanding how operational performance affects reverse logistics and competitive advantage by explaining resource relationships within organizations as they seek to gain comparative advantage. The theory further establishes a framework for interrogating how reverse logistics associated capabilities and outcomes impact a firm (Hunt & Morgan, 2005).

2.2.3 Diffusion of Innovation Theory

Diffusion of innovation theory recognizes that 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 characteristics namely compatibility, relative advantage, simplicity, observability and trialability 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 weaknesses of the theory are lack of causality, pro-innovation bias and heterophily (Rogers, 1976). Lack of causality means diffusion of innovation research lacks the ability to track variable changes over time. Pro-innovation bias assumes all innovations yield positive results and should wholesomely be adopted by everyone. Heterophily means separating the effect individual characteristics have on a system and the effect the system structure has on diffusion is complex (Rogers, 2003). This makes explaining the impact of environmental dynamics and power play among various business partners on the diffusion rate difficult.

Despite these limitations, diffusion of innovation theory will be useful in testing the extent to which adoption variations in process interventions affect innovation spread. Adoption variations will be established by measuring the degree to which innovation attributes influence diffusion rate. Therefore, the theory advances a basis to illustrate and forecast factors that accelerate or hinder innovations spread in understanding how process innovation influences reverse logistics and operational performance.

2.2.4 Institutional Theory

As the over-arching theory in this study, institutional theory views the structure of the formal organization as based on technology, resource dependencies and institutional forces (Scott, 2008). Institutions define how interactions among people take place using an informal process established by codes of conduct, behavior norms and conventions and their enforcement characteristics (North, 1991). Institutional structures and technologies determine transformational and transaction costs impacting production costs. For firms to compete, increased organizational legitimacy should be as a result of organizational isomorphism (Kostova, Roth & Dacin, 2008). Mechanisms for isomorphism have been categorized as coercive, mimetic and normative (DiMaggio & Powell, 2004).

The theory's full potential remains untapped when examining the tenacity and homogeneity of phenomena while ignoring dynamics of the external environment that bring institutional change (Dacin, Goodstein & Scott, 2002). Further, a lack of consensus on concepts and measurement systems poses the challenge of not having a standard research methodology based on the theory (Tolbert & Zucker, 1999). Similarly, a process approach to institutionalization is yet to be conceptualized and specified in most organizational analysis (DiMaggio & Powell, 2004).

Institutional theory is useful in explaining similarities in practice among firms brought about by isomorphic pressures; understanding obstacles on the spread and establishment of firm practices; conceptualization of business environments with respect to regulatory, cognitive and normative pillars; identifying relationships between the host environment and the firm; and understanding of business process using the ideas of legitimacy, institutional transition, upheaval and imperfection (Kostova, Roth & Dacin, 2008).

2.3 Reverse Logistics and Competitive Advantage

Research in reverse logistics has focused on adoption levels, factors influencing adoption or implementation barriers. Empirical research has indicated adoption at lower than average level (Abdullah et al., 2011; Bouzon et al., 2018; Prakash & Barua, 2015). According to Ho et al. (2012) key internal factors determining reverse logistics implementation were financial and human resources while external factors included cooperation with other firms. Abdulrahman et al. (2014) categorized reverse logistics implementation obstacles as management, financial, policy and infrastructure related. Studies have also identified inadequate apprehension of reverse logistics and percipience that capital requirements for reverse logistics actualization as high to be the major implementation barriers (Huang & Yang, 2014; Prakash et al., 2015). Genchev et al. (2011) and Meyer et al. (2017) indicated firm's ignore reverse logistics processes because they impose costs, hinder growth in productivity and impede competitiveness. Yet, according to Ravi and Shankar (2015) firms adopt reverse logistics practices to benefit from economic advantages associated with them.

Markley and Davis (2007) opined reverse logistics could lead to gaining competitive advantage, but implementation is complex due to process challenges and uncertainties. Hung-Lau and Wang (2009) while investigating the applicability of reverse logistics models and theories, revealed lack of economic support and absence of a preferential tax policy as impediments to the reduction of investment costs of reverse logistics. Jim and Cheng (2006) concluded that the loss on material costs due to discarding returned goods is less than the resources spent on reverse logistics. These studies suggest reverse logistics has an association with advantageously creating competitiveness but with contrasting results. Similarly, previous studies discussed reverse logistics as a singular approach to the implementation of reverse flow systems (He & Wang, 2005; Hung-Lau & Wang, 2009;

Rao & Holt, 2005; Govindan et al., 2015). In this study it was found to be worth studying reverse logistics as an intervention consisting of several approaches. Further studies prior have also considered studying reverse logistics as a sub-variable of an overall latent variable (Zhu, Sarkis & Lai, 2008; Ninlawan, Seksan, Tossapol & Pilada, 2010; Ochieng, Awino, Njihia & Iraki, 2016). In contrast Markley and Davis, (2007); Kumar and Putnam, (2008); Kwateng et al., (2014) posited that reverse logistics can be considered as an independent construct resulting in the creation of competitiveness. In view of the foregoing discussion the researcher posits the following:

Proposition 1: Reverse logistics has no significant influence on a firm's competitive advantage.

2.4 Reverse Logistics, Operational Performance and Competitive Advantage

Stock et al. (2006) established that reverse logistics programme achievement was influenced by how resources are committed by management. The resource advantage theory of competition posits that, harnessing unique resources assists firms to gain internal comparative advantage, and after build competitive advantage at the marketplace. Firms' gain comparative advantage when resources in their control help to generate and implement strategies resulting in highly efficient and effective operations (Barney, 1991).

Stock et al. (2006) also posited that a business unit's customer satisfaction levels, cost reduction efforts, revenues and profits are directly and positively affected by how product returns are managed. Cannella, Bruccoleri and Framinan (2016) posited that reverse logistics results in creating order and stock stability and therefore firms need to invest in returns management. Similarly, reverse logistics practices have potential to increase customer value and reduce customer's risk when purchasing products (Dias & Braga Jr., 2016). Thus, the need to initiate sustainability creating capabilities in reverse logistics such that competitive advantage is created is essential for firms (Russo & Cardinali, 2012; Prakash & Barua, 2015). Reverse logistics and a firm's competitory position therefore have a relationship contingent on achieving internal operational proficiency but the strength of the relationship is not known to have been investigated before. Thus the researcher posits the following:

Proposition 2: Operational performance has no significant influence on the association between reverse logistics and a firm's competitive advantage.

2.5 Reverse Logistics, Process Innovation 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 in the short and long-run. According to Porter (2008) innovations should be considered at a strategic and operational level. He differentiated operational efficiency and strategy and argued both are critical components for competitive advantage. 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 competitive advantage 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 posits the following:

Proposition 3: Process innovation has no significant influence on the association linking reverse logistics and operational performance.

2.6 Reverse Logistics, Process Innovation, Operational Performance and Competitive Advantage

Huang and Yang (2014) argued that a firm's reaction to the presence of institutional pressures influences how reverse logistics and external organizational performance associate. Rogers and Tibben-Lembke (2001) observed that reverse logistics can assist a firm's value system in identifying problem areas and defect patterns, hence minimizing returned products. Value chains organized innovatively can create higher value than competitors (Porter, 2008). Such a value system has direct and indirect benefits (De Brito et al., 2005). Direct benefits comprise income from re-sold products, spare parts savings or savings realized from de-manufactured parts or recycled materials. The indirect benefits come from improved corporate image due to recycling of waste.

Empirical literature has suggested reverse logistics contributes to generating competitiveness for firms but with disparate results (Hung-Lau & Wang, 2009; Jim & Cheng, 2006; Prakash & Barua, 2015). Similarly, empirical evidence suggests a relationship among reverse logistics, process innovation and operational performance (Christmann, 2000; Huang & Yang, 2014; Morgan et al. 2016). Literature has also linked reverse logistics, operational performance and competitive advantage (Jack et al., 2010; Russo & Cardinali, 2012; Cannella et al., 2016). These studies have shown reverse logistics, process innovation and achieving operational proficiency have an influence on a firm's competitory position. On this basis the researcher proposes the following:

Proposition 4: Process innovation and operational performance have no significant moderated-mediation effect on the association linking reverse logistics and a firm's competitive advantage.

Proposition 5: Reverse logistics, process innovation and operational performance have no significant effect on a firm's competitive advantage.

2.7 Recapitulation of Knowledge Gaps

Table 2.1 shows a recapitulation of studies done in reverse logistics, process innovation, operational performance and competitive advantage from various theoretical perspectives and gaps in knowledge addressed in this research.

Table 2.1 ***Recapitulation of Knowledge Gaps***

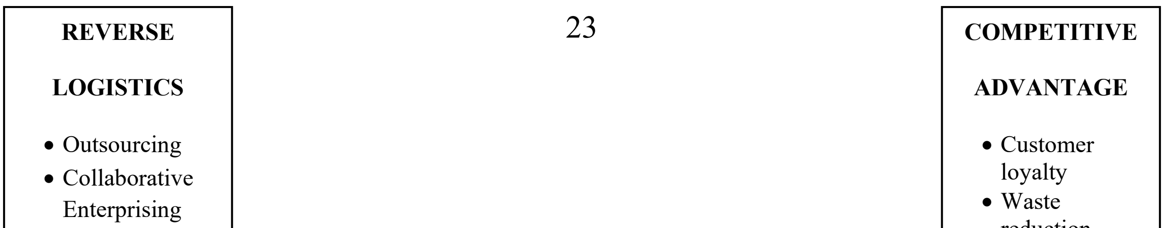
Researcher (s)	Focus	Methodology	Findings	Knowledge Gap
Abdulrahman, Gunasekaran, & Subramanian, (2014)	Reverse Logistics Adoption	Based on a survey on reverse logistics implementation barriers among Chinese manufacturers using cross-sectional designs	Reverse logistics implementation barriers include insufficient knowledge and awareness of reverse logistics and a perception that reverse logistics require large capital commitment to implement	Lack of acknowledgement on the critical role of reverse logistics and that reverse logistics require considerable initial costs

		with regression modeling		of adoption and it is demanding and time-consuming.
Huang & Yang, (2014)	Environmental Performance, Sustainable Development, Economic Performance,	Hierarchical regression analysis is used to explain how institutional pressures moderate innovation in reverse logistics and performance.	Innovation in reverse logistics positively impacts environmental and economic performance. Further institutional pressures moderate innovation in reverse logistics and environmental performance.	Inadequate understanding of how reverse logistics determines future performance of the organization
Hunt & Mudhavaram, (2012).	Competitive Advantage	Review of literature on institutional theory	The paper identifies five conceptual frameworks that are posited to have positive theoretical foundations using the resource advantage theory of competition	Competitive advantage has continued to raise philosophical and theoretical considerations among scholars including those in reverse logistics
Jack, Powers, & Skinner, (2010)	Reverse logistics scheduling & Cost saving	Based on a survey of 295 retailers investigating how customer and retailer associated antecedence of reverse logistics capabilities affect cost savings.	Creating reverse logistics capabilities to gain competitive advantage is self evident for firms as it leads to cost savings. Opportunism has negative effect on reverse logistics capabilities.	Lack of explanatory research linking reverse logistics, process innovation and competitive advantage
Armbruster, Bikfalvi, Kinkel & Lay, (2008)	Process and Organizational Innovation,	A survey of 1450 German manufacturing firms.	Within one and the same sample, different methods of measuring innovation in organizations have yielded varied results.	Lack of research on approaches to be used in measuring innovation in organizations on a large scale.
Scott, (2008)	Institutional Theory	Review of literature on institutional theory	There is a group of scholars developing and testing institutional arguments from intra-organization and inter-organization perspective,	The non-existent of research examining the effects of institutional pressures on reverse logistics

Source: Research Data, 2020

2.8 Conceptual Structure and Hypotheses

Figure 2.1 shows that reverse logistics strategies include outsourcing, collaborative enterprise, green strategies and product-life cycle approach. Operational performance measured using cost, time/speed, operations flexibility, dependability and quality intervenes the association relating reverse logistics and the firm's competitory position. Process innovation is measured using process reengineering, value chain restructuring, resource deployment, product redesign, and implementing information systems and has a moderating outcome on the association linking reverse logistics and gaining operational proficiency. Competitive advantage is measured using customer loyalty, waste reduction, revenue increase, brand recognition and market share.



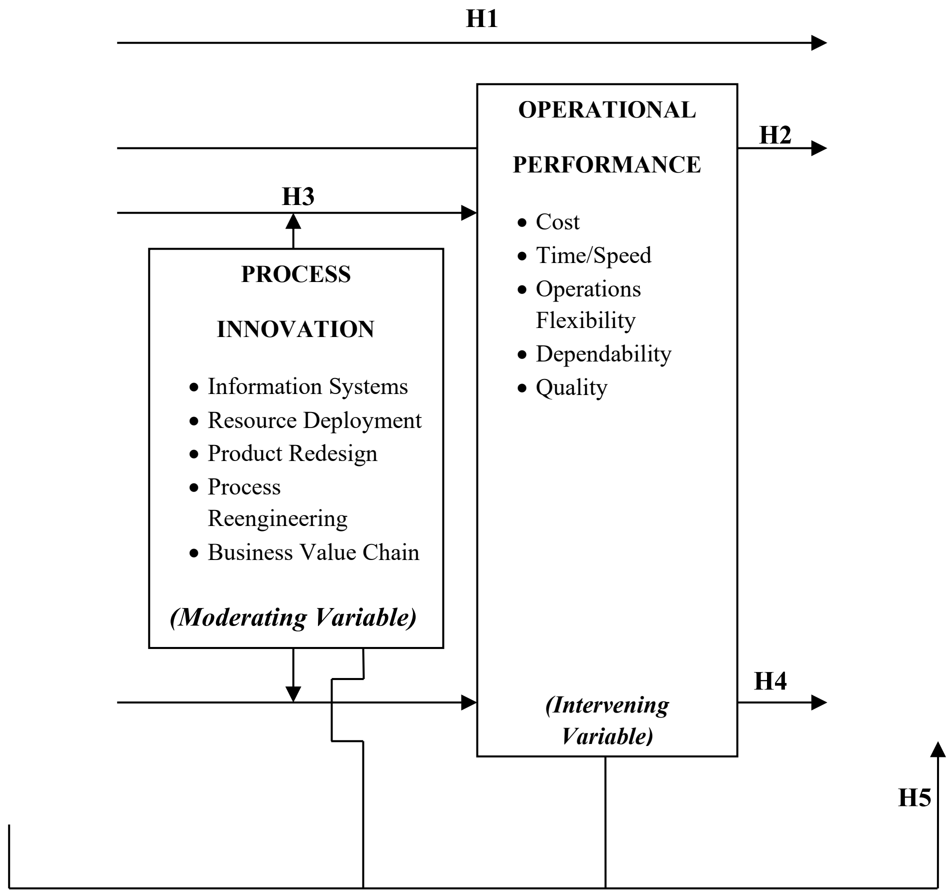


Figure 2.1. **Conceptual Model**

Based on figure 2.1 the hypotheses to establish how reverse logistics generates competitive advantage and how process innovation and operational performance, moderate and mediate respectively the interactions among the variables are summarized as follows.

H1: Reverse logistics has no significant influence on a firm's competitive advantage.

H2: Operational performance has no significant mediating influence on the relationship between reverse logistics and a firm's competitive advantage.

H3: Process innovation has no significant moderating influence on the relationship between reverse logistics and operational performance.

H4: Process innovation and operational performance have no significant moderated-mediation influence on the relationship between reverse logistics and a firm's competitive advantage.

H5: Reverse logistics, process innovation and operational performance have no significant joint influence on a firm's competitive advantage.

CHAPTER THREE: RESEARCH METHODOLOGY

3.1 Introduction

This chapter described the philosophical grounding of the research, research design, population of the study, sample and sampling design, research instruments, data collection and analysis procedures. The chapter also discussed how the operationalization of the study variables was undertaken and the validity and reliability tests used. The chapter concluded by discussing data diagnostic tests used and analysis.

3.2 Research Philosophy

Common approaches used in research philosophy are interpretivism, realism and positivism. Interpretivism portends that the actual state of existence and the researchers notional idea are inseparable. Interpretivism aims at grasping individual and shared meanings, where understanding is a never ending hermeneutical process (Clarke, 2009). Qualitative interpretations are based on the researcher's experience such that reality becomes a social construct (Weber, 2004).

Realism is built upon an opinion that a "real" world exists independent of any one person and the world is imperfectly and probabilistically apprehensible as founded on abstractions of people's intelligence (Healy & Perry, 2000). In realism a perception is studied as a window for understanding a reality by developing a picture of reality through triangulation with perceptions beyond that perception. Realism is more on theory-construction rather than testing how applicable a theory is to a population.

Positivists seek the goal of explanation through universal law, hypotheses testing and prediction. In positivism beyond the human mind there exists objective reality such that independent of the researcher are inherent qualities in the research object and reality can be measured using quantitative data (Weber, 2004). This study was grounded on the positivism as it required explanation and understanding of hypothesized systematic association of variables (Clarke, 2009).

3.3 Research Design

This study sought to deploy a correlation cross-sectional survey. The study was correlation as it was concerned with determining if two or more variables covary. In correlation research no attempt to manipulate or control the variables is made. Correlation research aims at 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 single duration. Secondly, cross-sectional research also permitted the creation of heterogeneous population clusters in understanding the underlying group characteristics. Thirdly, these studies also allow for comparison among many variables in a study (O'Cass & Viet, 2007). Finally, cross-sectional designs are appropriate where the study requires the collection of data pertaining to specific variables in a study.

3.4 Population of the Study

The population of this study consisted of all manufacturing firms in Kenya. The researcher established that KAM has the most comprehensive listing of manufacturing firms in Kenya. As at 30th June 2018 there were 903 firms registered as KAM members in the manufacturing sector. The unit of analysis was the manufacturing firm. Appendix 3 shows the distribution of these firms per manufacturing sector.

KAM membership is 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 NEMA in implementing environmental management activities. 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.

3.5 Sample and Sampling Technique

Based on the degree of precision, the confidence level and the degree of variability required for this study, sample size was established as follows:

$$n = \frac{N}{1 + N(e)^2}$$

Where: n = sample size required

N= population

e = precision level assuming 5 percent significance level.

Source: Yamane, (1967)

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). Ho et al. (2012) used a sample of 300 in Hong Kong. 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. Appendix 3 provides details of the sample stratification and appendix 4 provides a listing of sampled firms per manufacturing sub-sectors.

3.6 Data Collection

Using a structured questionnaire, primary data was gathered. The questionnaire had five sections namely; organization profile; reverse logistics; process innovation; operational performance; and competitive advantage. Reverse logistics and process innovation were measured using a 5 point Likert-type scale while operational performance and competitive advantage were measured using direct measures. Self administered questionnaires were dropped and picked by the researcher and data collection assistants. Targeted respondents were the managing director/owner, the operations/supply chain director/manager or their equivalent in the targeted firms because of their orientation towards strategic returns management responsibilities.

Academia and industry experts participated in the development of the data collection instrument to ensure validity. Pre-testing of the questionnaire was done using thirty (30) members of the sample. The study used single respondent in each firm as reliability and validity of single informant research is as good as multiple informant research (O'Cass & Viet, 2007).

3.7 Research Variable Operationalization

The researcher operationalized reverse logistics and process innovation, using multi-item indicators. Operational performance and competitive advantage were measured using direct measures. Table 3.1 provides further details of how the variables were operationalized.

For reverse logistics and process innovation, the likert-type scale was used in determining these measures. Presence of an underlying continuous variable characterizing the respondents' value on a belief, opinion or attitude is presumed in likert-type scaling where data cannot be gathered definitely, precisely or categorically (Clason & Dormody, 1994). Likert-type scaling is therefore used as an alternative in generating relevant data for understanding such variables (Boone & Boone, 2012).

Table 3.1 ***Operationalization of Study Variables***

Latent Variable	Operational Definition	Constructs	Indicators	Source / Authority	Measurement	Scale	Questionnaire Item
Reverse Logistics	Reverse logistics is operationally defined as the average rating of a multi-item score on the five point Likert type scaling for the pre-defined sub-constructs.	Outsourcing to third party	Multi-item indicators as shown in questionnaire – Section B	He and Wang, (2005); Rao and Holt, (2005); De Brito et al., (2005).	Five Point Likert-type Scale	Interval	Section B – Question 2.1, 2.2 and 2.3
		Collaborative enterprise					
		Green strategies					
		Product – Life Cycle Approach					
Process Innovation	Process innovation is operationally defined as the average rating of a multi-item score on the five point Likert type scaling for the pre-defined sub-constructs.	Information systems	Multi item indicators as shown in questionnaire - Section C	Jayaraman and Luo, (2007); Armbruster et al., (2008); Porter (2008)	Five Point Likert -type Scale	Interval	Section C – Questions 3.1
		Resource deployment					
		Product redesign					
		Process reengineering					
		Business value chain					
Operational Performance	Operational performance is a multi-item assessment of direct measures of the per unit cost of production, order fill rate, number of customer complaints, number of product lines, down-time and average lead-time	Cost	Per unit variable cost of production	Brah and Ying-Lim, (2006); De Souza and Brito, (2011); Chavez et al., (2013)	Direct measures of operational performance using numbers, percentages or ratios	Ratio	Section D – Questions 4.1
		Quality	Order fill rate				
			No. of customer complaints				
		Delivery speed	Average lead-time				
		Flexibility	No. of product lines				
		Dependability	Down-time				
Competitive Advantage	Competitive advantage is a multi-item assessment of direct measures of customer retention rate, defect rate, percentage increase in revenue, percentage increase in market share and profit margins.	Customer loyalty	Customer retention rate	Markley and Davis, (2007); Hunt and Madhavaram, (2012)	Direct measures of competitive advantage using numbers, percentages or ratios	Ratio	Section E – Questions 5.1
		Waste reduction	Defect rate				
		Revenue increase	Percentage revenue increase/decrease				
		Market share	Percentage market share increase/decrease				
		Brand recognition	Profit margins				

Source: Research Data, 2020

3.8 Reliability and Validity Tests

Cronbach's alpha coefficients were computed for all variables in the model in examining reliability. In the opinion of Hair, Money, Samouel and Page (2007) a Cronbach alpha coefficient ≥ 0.7 represents good association among data instruments. Communalities were then assessed using Principal Component Analysis (PCA) to determine the magnitude with which the variance in each of the latent constructs and variables were explicated by the questionnaire items (Field, 2009). Pallant (2007) suggested that communalities values should be > 0.3 for them to have sufficient explanatory power.

Content validity evaluates the level of similarity between the questionnaire items picked to comprise a totalized scale and its conceptual interpretation. The aim is to make sure that the choice of scale items goes beyond considering only empirical issues, to include practical and theoretical circumstances. Content validity was checked using a panel of expert's opinion in the field of reverse logistics (Hair, Black, Babin & Anderson, 2014).

Convergent validity which establishes how indicators of a particular construct merge or share a larger percentage of variance was measured using the standardized factor loading for each of the five objectives of the study. For these the factor loadings were expected to be > 0.5 for acceptable convergent validity. Convergent validity was measured using Average Variance Extraction (AVE) method. For these the AVE for each of the latent constructs was expected to be > 0.5. Discriminant validity examines how constructs perceived not to be theoretically associated are indeed not associated. The AVE was expected to be > Maximum Shared Variance (MSV) for each of the latent variables to be considered not to be theoretically associated.

3.9 Data Diagnostics

Credible results can be obtained if the data set has high level of accuracy in data entry; issues of missing data are addressed; level of fit between data set and assumptions of normality, collinearity, heteroscedasticity and autocorrelation are checked; and variable transformations for outliers and perfect or near perfect correlations are performed (Tabachnick & Fidell, 2013). To achieve accuracy in data entry, an examination of descriptive statistics and graphic representation of variables was done (Hair et al., 2014). T-test between missing and non-missing data sets was done to determine significant differences between data sets. Where significant differences were observed, mean substitution method was used for non-missing data items.

Outliers were examined using a univariate identification method where the distribution formed by the observations for each variable in the analysis is first converted to a standard normal distribution. Each observation is then tested to see the extent to which its Standard Deviation (SD) is significantly different from the mean. In the opinion of Hair et al. (2014) those observations with standard scores > 2.5 or < -2.5 are considered outliers.

Preceding the factor analysis was the Kaiser-Meyer-Olkin (KMO) test for sampling adequacy and Bartlett"s test of sphericity. The KMO statistic varies between 0 and 1. According to Kaiser, Rice, Little & Mark (1974) the indices of factorial simplicity using KMO test may be evaluated as follows. Values < 0.50 are unacceptable; 0.50s range are considered miserable; 0.60s range are mediocre; 0.70s range are middling; 0.80s range are meritorious and 0.90s range are considered marvelous. Based on this acceptable KMO values should be above 0.70. Values close to 1 indicate that the patterns of correlations are generally succinct therefore factor analysis would realize unambiguous and reliable factors.

Sphericity requires the p-value to be < 0.05. If the value is < 0.05 indicates that data reduction techniques can truncate the data in a statistically meaningful way.

Kolmogorov-Smirnov test and Shapiro-Wilk test were used for testing normality. The tests require the p-value to be > 0.05 to have ample evidence to suggest normality in the distribution (Field, 2013). Variance Inflation Factor (VIF) was used to diagnose collinearity where the VIF for the independent variables were expected to be < 5 if the variable is not collinearly related to the other regressor variables (Tabachnick & Fidell, 2013). The VIF was calculated using the formula

$$VIF = \frac{1}{(1 - R^2)}$$

Where:

VIF = Variance Inflation Factor

R^2= The resultant co-efficient of determination

Heteroscedasticity was tested using the Koenker's test, where the hypothesis that no significant differences exist among group variances was tested. For the test, if the p-value was > 0.05 homoscedasticity was assumed.

Durbin-Watson test was used to test for autocorrelation. Generally, if the test statistic (D) = 2 it means no autocorrelation exists in the sample. If test statistic is < 2 this indicates positive autocorrelation and if it is > 2 then we have negative autocorrelation (Tabachnick & Fidel, 2013). Durbin-Watson statistic is calculated using the formula below.

$$d = \frac{\sum_{t=2}^{t=n}(\hat{u}_t - \hat{u}_{t-1})^2}{\sum_{t=1}^{t=n}\hat{u}_t^2}$$

Where:

d = Durbin-Watson statistic

$\hat{u}_t$ = residual of the n^{th} observation

$\hat{u}_{t-1}$ = residual of the $n^{th} - 1$ observation

In the event the statistic lies in the indecision range, a modified Durbin-Watson statistic to assess the extent of negative or positive serial autocorrelation is calculated by use of the formulae below.

$$\sqrt{n}\left(1 - \frac{1}{2}d\right) \approx N(0, 1)$$

Where:

n = number of observations

d= first order Durbin-Watson statistic

This modified statistic standardizes the initial Durbin-Watson statistic to conform to the properties of the standard normal distribution.

Before conducting the hypothesis tests for each hypothesis, Confirmatory Factor Analysis (CFA) was performed to ascertain the overall model fit. Checking for the overall model fitness requires investigating three parameters. First was the absolute model fitness which was evaluated using the chi-square value, the p-value, Root Mean Square Error of Approximation (RMSEA) and Goodness of Fit Index (GFI). For a good absolute fit model the chi-square value is expected to be small, probability level < 0.05, RMSEA < 0.08 and GFI > 0.90. Second was the incremental model fitness which was evaluated using Adjusted Goodness of Fit Index (AGFI), Comparative Fit Index (CFI), Normed Fit Index (NFI) and the Turker Lewis Index (TLI). For a good incremental fit, AGFI > 0.90, CFI > 0.90, 0.8 < NFI < 1.00 and TLI > 0.9. Third was the parsimonious model fitness which was calculated by finding the ratio between chi-square value and the degrees of freedom. This ratio refers to the minimum discrepancy and is commonly denoted as CMIN/DF. For a good parsimonious fit CMIN/DF < 5 (Hooper, Coughlan & Mullen, 2008).

Common Method Variance (CMV) determines the spurious correlation resulting from ascertaining the degree to which every variable was assessed using the same technique especially when a single respondent evaluates all the variables in the research using Common Latent Factor (CLF) method. CLF is a covariant of the measure of assumed source of the method variance (Lindell & Whitney, 2001). The common variance determined by squaring the common factor of each path before standardization. This value should be < 0.50. A more efficient way of performing CLF method is by getting the difference between the standardized regression weights with the common methods variables in the model and comparing them with standardized regression weights when the common methods variables is not in the model. The difference between the two weights should be < 0.20. If the differences are < 0.20 it means therefore that it will not be necessary to include the common method latent variable while performing the hypothesis test.

3.10 Data Processing and Inquiry

This study proposed to use covariance-based SEM in the processing of the data (Allen & Seaman, 2007). Hair et al., (2014) posits that Analysis of Moment Structures (AMOS) uses SEM to validate and give explanatory power to conceptual models that involve perceptual data. SEM is more robust than standard approaches because within the same model one or more variables measured using multiple indicators are analyzed to determine model interaction, correlations and measurement errors (Tabachnick & Fidel, 2013). In order to achieve this, path analysis was used to link study variables. Figure 3.1 below illustrates the overall model.

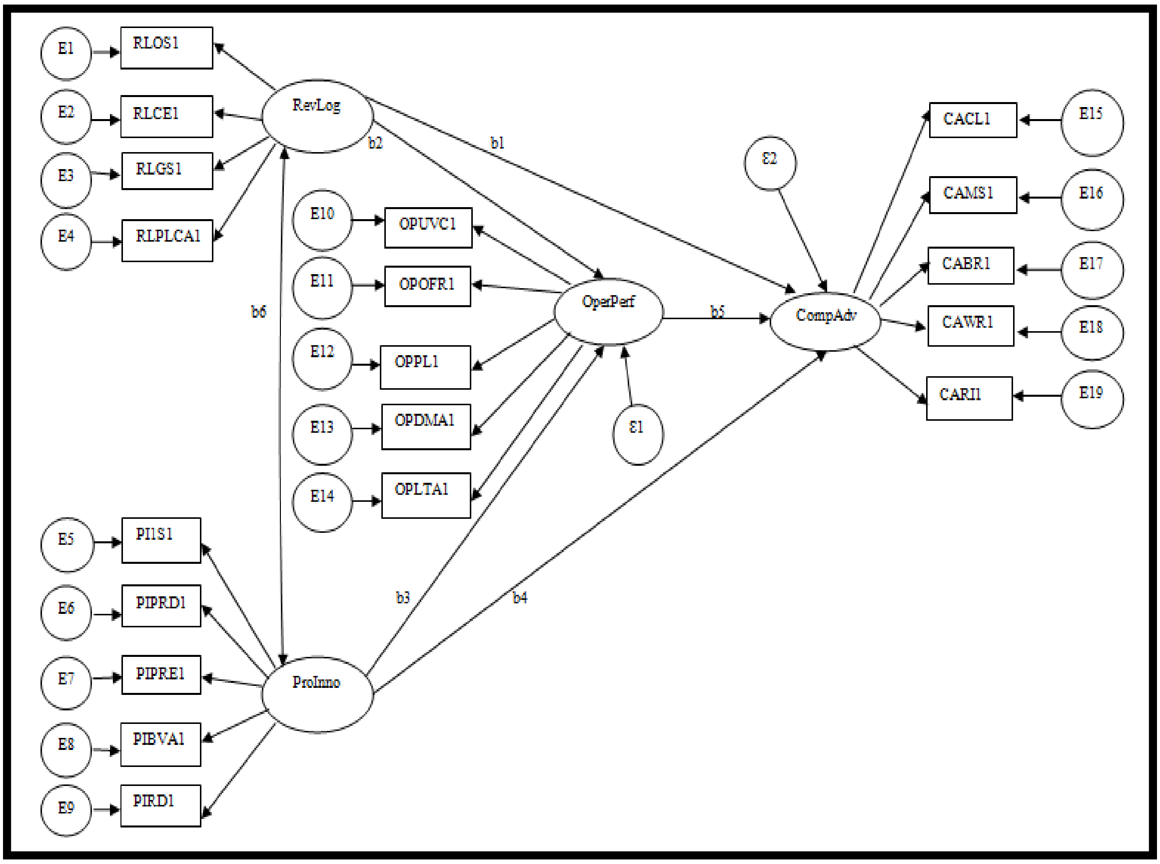


***Figure 3.1*. Overall Model Path Diagram**

Where:

RevLog = Reverse logistics
ProInno = Process innovation
OprPerf = Operational performance
CompAdv = Competitive advantage

E_{is} = Residuals on latent constructs
$\mathcal{E}_{is}$ = Residual on variables
b_{is} = Coefficients of the model

Based on figure 3.1 SEM was used to diagrammatically represent the proposed measured and structured relationship among the variables where reverse logistics was the independent variable and operational performance mediated the interaction linking reverse logistics and the firm's competitory position. From the figure process innovation moderated the association linking reverse logistics and operational performance. Similarly the moderated-mediation effect of process innovation and operational performance on the association linking reverse logistics and the firm's competitory position were tested using the model. To further understand these relationships an examination of the effect of reverse logistics, process innovation and operational performance as independent variables on competitive advantage was conducted using the path diagram. Figure 3.2, 3.3, 3.4, 3.5 and 3.6 provided the specific path diagrams for each of the relationships as seen in the overall model in figure 3.1.

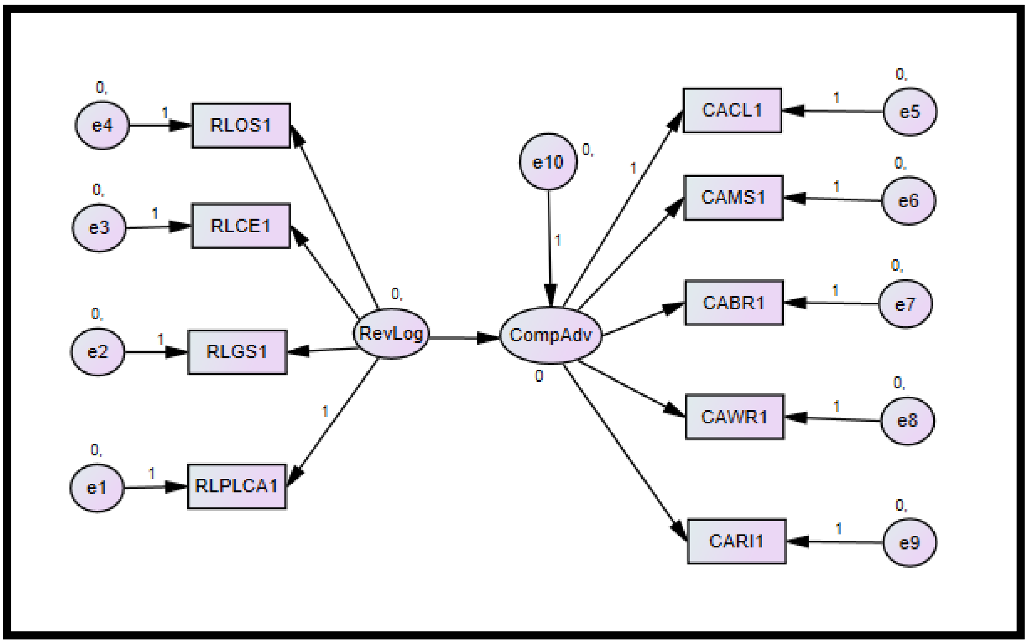


Figure 3.2. **Path Diagram showing the Association linking Reverse Logistics with Competitive Advantage**

Figure 3.2 above demonstrated the hypothesized relationship between the latent variable reverse logistics and competitive advantage represented by the oval nodes Revlog and CompAdv respectively in the diagram. Reverse logistics 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. Competitive advantage was measured using customer loyalty, market share, brand recognition, waste reduction and revenue increase. These were diagrammatically represented using the rectangular nodes CACL1, CAMS1, CABR1, CAWR1 and CARI1 respectively. Figure 3.3 below reveals the path diagram demonstrating the hypothesized association linking reverse logistics, operational performance and a firm's competitive advantage.

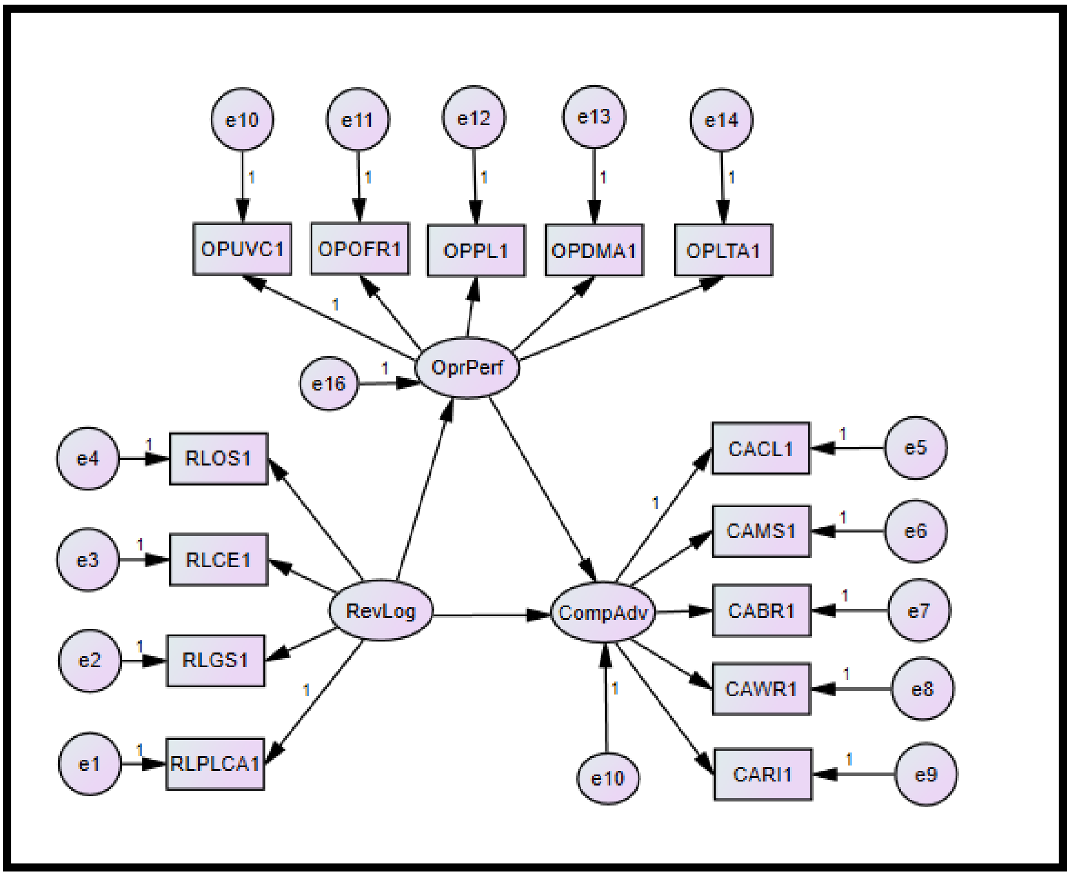


Figure 3.3. **Path Diagram for the Association linking Reverse Logistics, Operational Performance and Competitive Advantage**

Figure 3.3 suggested that operational performance mediated the association of reverse logistics with competitive advantage. Operational performance represented in the diagram as an oval node labeled 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. Reverse logistics and competitive advantage and their latent constructs were labeled the same way as in figure 3.2. Figure 3.4 below shows the path diagram demonstrating the hypothesized association linking reverse logistics, process innovation and operational performance.

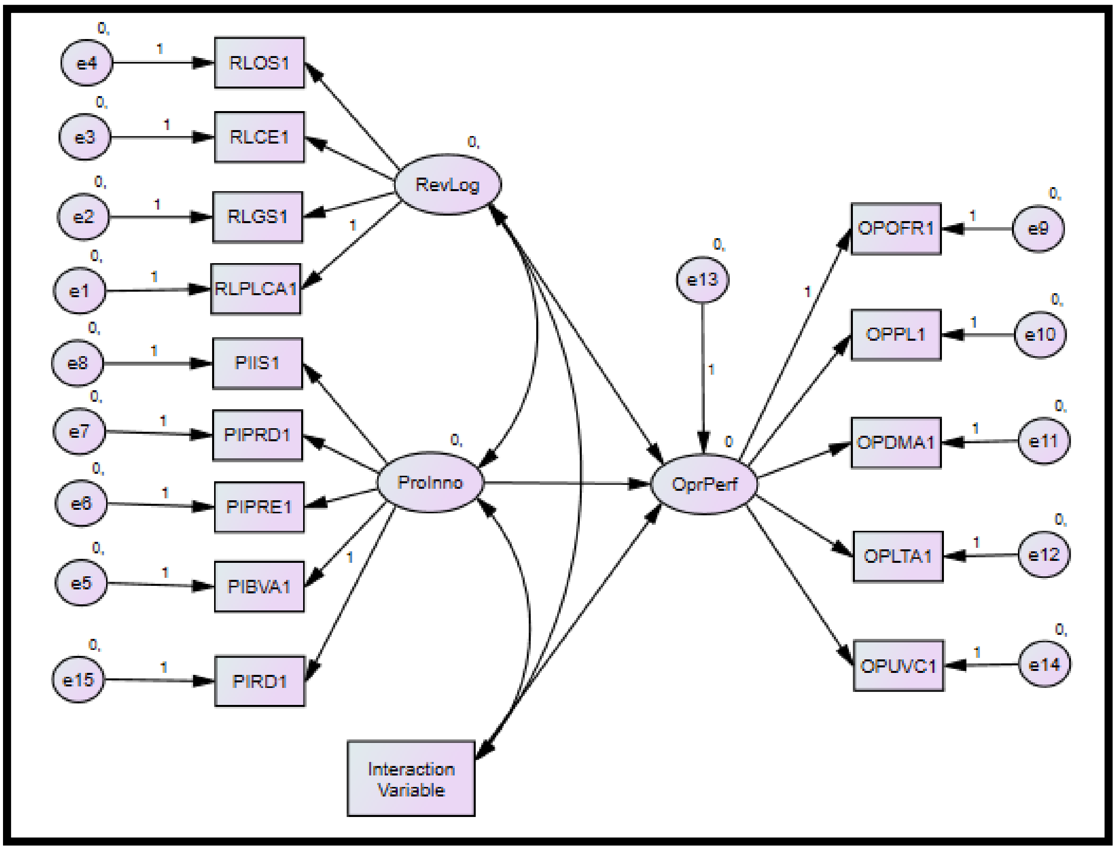


Figure 3.4. **Path Diagram for the Association among Reverse Logistics, Process Innovation and Operational Performance**

According to figure 3.4 above, process innovation was hypothesized to moderate the association linking reverse logistics and operational performance. Process innovation was diagrammatically represented as an oval node labeled ProInno and measured using the latent constructs information systems, resource deployment, product redesign, process reengineering and business value chain. These were represented in the diagram using rectangular nodes labeled PIIS1, PIRD1, PIPRD1, PIPRE1 and PIBVA1 respectively. Figure 3.2 and 3.3 discussed how the latent variables and constructs for reverse logistics, operational performance and competitive advantage were labeled. Figure 3.5 shows the path diagram demonstrating the hypothesized moderated-mediation relationship among reverse logistics, process innovation, operational performance and competitive advantage.

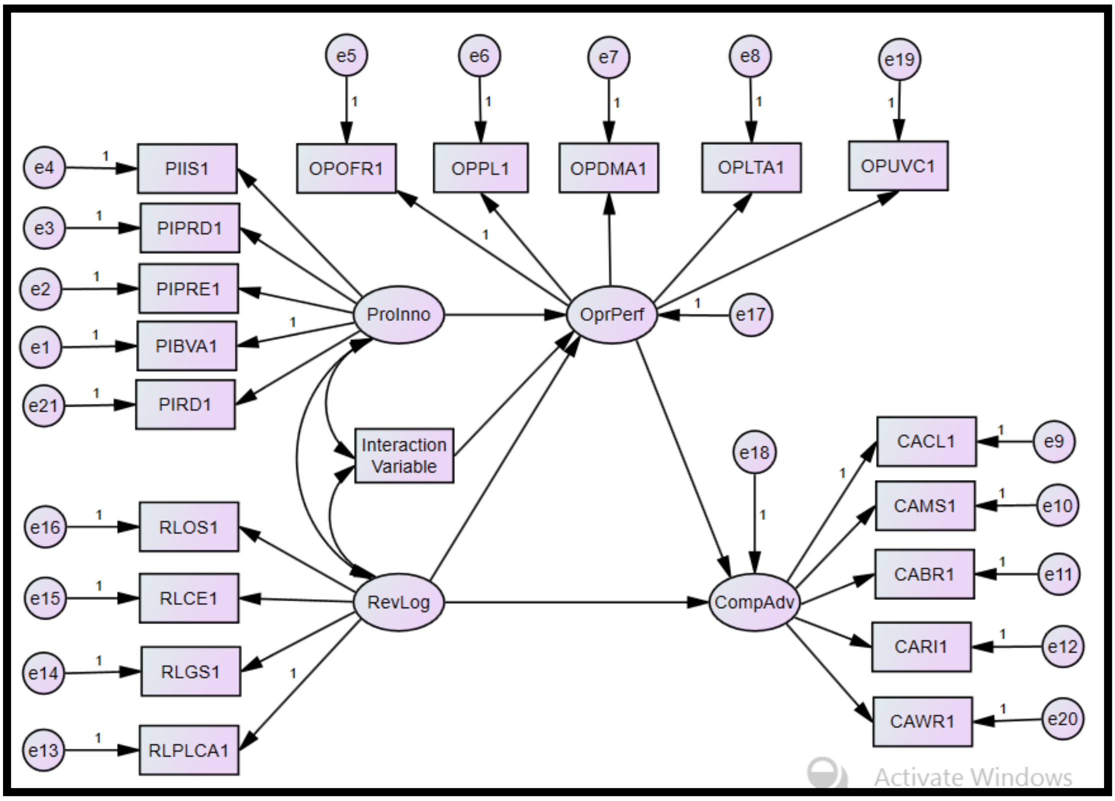


Figure 3.5. **Path Diagram for the Moderated-Mediation Relationship among Reverse Logistics, Process Innovation, Operational Performance and Competitive Advantage**

According to figure 3.5 above, process innovation was hypothesized to moderate the association linking reverse logistics and operational performance and at the same time operational performance mediated the interaction linking reverse logistics and improvement of a firm's competitory position resulting in the moderated-mediation effect. Latent variables and constructs labels used followed the convention used in figure 3.2, 3.3 and 3.4. Finally figure 3.6 shows the path diagram demonstrating the hypothesized combined-effect relationship among reverse logistics, process innovation, operational performance and competitive advantage.

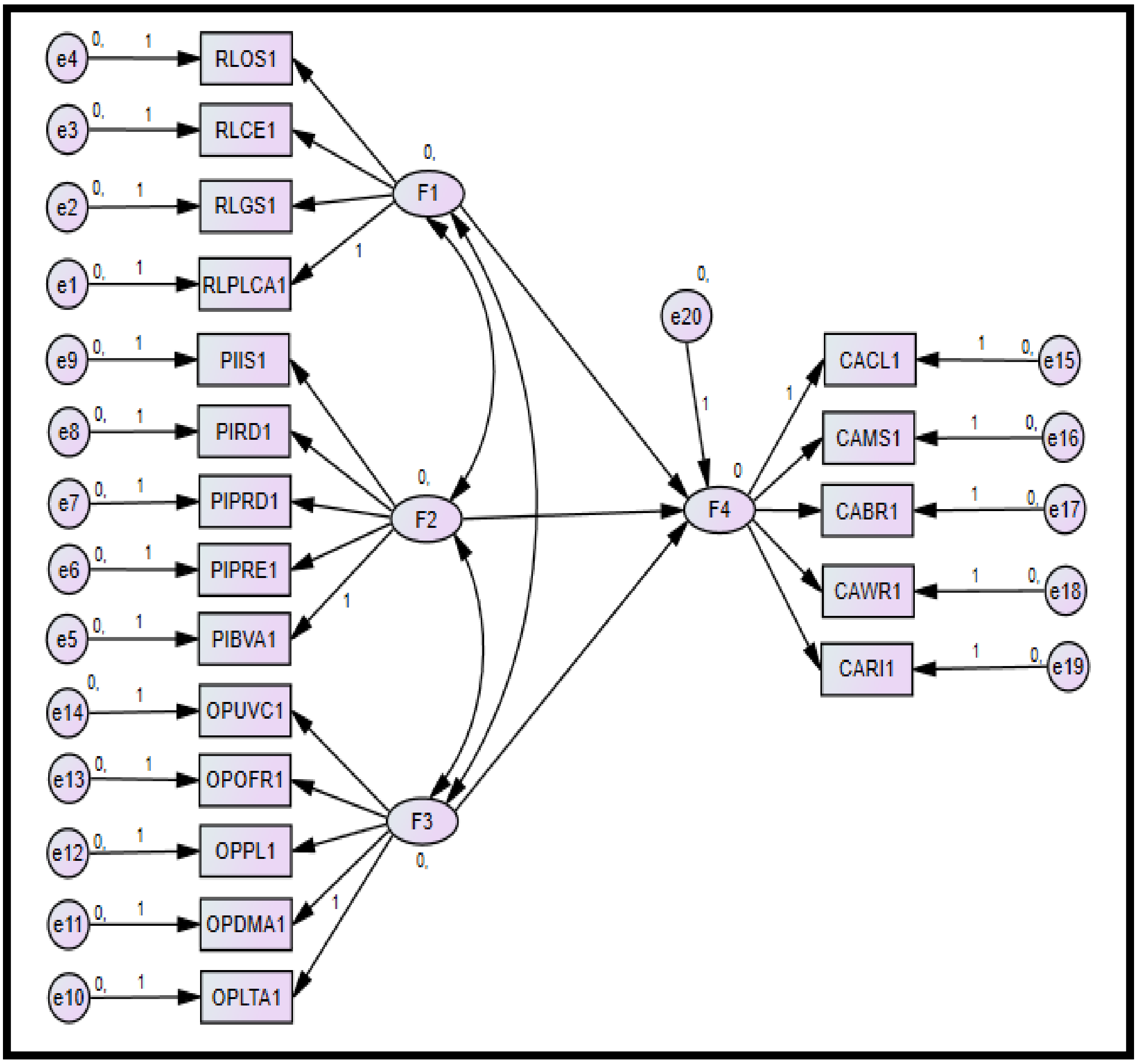


Figure 3.6. **Path Diagram for the Combined Effect of Reverse Logistics, Process Innovation and Operational Performance on Competitive Advantage.**

Figure 3.6 above, shows the interaction of reverse logistics, process innovation and operational performance as predictor variables and competitive advantage as the outcome variable in understanding the combined effect. Latent variables and constructs labels used followed the convention used in figure 3.2, 3.3 and 3.4. Table 3.2 summarizes the analysis technique used for each objective.

Table 3.2 ***Summary Table of Data Analysis Techniques per Objective***

Objective	Hypothesis	Data Analysis Technique	Decision Criteria
Objective 1: To establish the influence of reverse logistics on competitive advantage.	**H1:** Reverse logistics has no significant influence on a firm's competitive advantage.	Structural Equation Modeling. (SEM). Significance of Standardized Root Mean Square (SRMR) residual and path coefficient.	Hypothesis is rejected if p-value of path coefficients is less than 0.05
Objective 2: To determine the influence of operational performance on the relationship between reverse logistics and a firm's competitive advantage.	**H2:** Operational performance has no significant mediating influence on the relationship between reverse logistics and a firm's competitive advantage.	Structural Equation Modeling. (SEM). Significance of Standardized Root Mean Square (SRMR) residual and path coefficient.	Hypothesis is rejected if p-value of path coefficients is less than 0.05
Objective 3: To determine the influence of process innovation on the relationship between reverse logistics and operational performance.	**H3:** Process innovation has no significant moderating influence on the relationship between reverse logistics and operational performance.	Structural Equation Modeling. (SEM). Significance of Standardized Root Mean Square (SRMR) residual and path coefficient	Hypothesis is rejected if p-value of path coefficients is less than 0.05
Objective 4: To examine the conditional indirect effect on the relationship among reverse logistics, process innovation and operational performance on a firm's competitive advantage.	**H4:** Process innovation and operational performance have no significant moderated-mediation influence on the relationship between reverse logistics and a firm's competitive advantage.	Structural Equation Modeling. (SEM). Significance of Standardized Root Mean Square (SRMR) residual and path coefficient	Hypothesis is rejected if p-value of path coefficients is less than 0.05
Objective 5: To examine the joint effect of reverse logistics, process innovation and operational performance on a firm's competitive advantage.	**H5:** Reverse logistics, process innovation and operational performance have no significant joint influence on a firm's competitive advantage.	Structural Equation Modeling. (SEM). Significance of Standardized Root Mean Square (SRMR) residual and path coefficient.	Hypothesis is rejected if p-value of path coefficients is less than 0.05

Source: Researcher, (2020)

CHAPTER FOUR: DESCRIPTIVE STATISTICS AND DATA DIAGNOSTICS

4.1 Introduction

This chapter analyzed the descriptive statistics and data diagnostics performed before examining the interaction among reverse logistics, process innovation, operational performance and competitive advantage. The chapter began by evaluating the response rate, non-response bias and the homogeneity of variance. The chapter then examined the reliability and validity of the instrument used in gathering data. The chapter proceeded by giving descriptive statistics that summarize descriptive coefficients of the data set. Further the chapter discussed the results of outlier, normality, autocorrelation, multicollinearity and heteroscedasticity tests. The chapter then presented the results of CFA in assessing model fitness. The chapter concluded by conducting CMV in order to check for spurious correlation between variables as a result of using similar methods to measure each variable particularly where a single respondent evaluated all the research variables.

4.2 Background of Research

The research aimed to examine the relationships among reverse logistics, process innovation, operational performance and competitive advantage among Kenyan manufacturing firms. Specifically, the study sought to establish the influence of reverse logistics on competitive advantage among the manufacturing firms. The second specific objective sought to determine the extent to which operational performance mediates the association linking reverse logistics and a firm's competitive advantage.

Thirdly, the study aimed at determining the moderating effect of process innovation on the association linking reverse logistics and operational performance. Fourth, the study examined the moderation-mediating effect of process innovation and operational performance on the association linking reverse logistics, on a firm's competitive advantage. Lastly, the study examined the joint effect of reverse logistics, process innovation and operational performance on competitive advantage of firms. The study context was Kenyan manufacturing firms that are members of KAM. Given the research background above the response rate, non-response bias and homogeneity of variance are examined in the ensuing sub-sections.

4.2.1 Response Rate

A total of 340 questionnaires were circulated to respondents out of which 175 were filled and returned. This represented a response rate of 51.5 percent. Although high response rates (> 70 percent) are preferable Mugenda and Mugenda (1999) other studies have shown that results from studies with response rates as low as 20 percent have no statistically significant difference with those of high response rates (Keeter, Kennedy, Dimock, Best & Craighill, 2006: Curtin, Presser & Singer, 2000).

A detailed scrutiny of the questionnaires revealed that 24 had more than 15 percent of data missing on key variables of the study. Therefore of the 175 questionnaires, 151 were found to be useful for further statistical analysis. This represents an adjusted response rate of 44.4 percent. Table 4.1 below recapitulates the response rate per manufacturing sub-sector.

Table 4.1 ***Response Rate per Manufacturing Sub-sector***

Manufacturing Sub-sector	Sample Size	Responses	Response Rate (%)	Usable	Adjusted Response Rate (%)
Building, Mining and Construction	15	13	86.7%	11	73.3%
Food & Beverage Sector	88	42	47.7%	33	37.5%
Fresh Produce	5	5	100.0%	5	100.0%
Chemical and Allied Sector	34	15	44.1%	12	35.3%
Energy, Electrical and Electronics	22	9	40.9%	8	36.4%
Leather and Footwear	3	3	100.0%	3	100.0%
Metal and Allied Sector	36	24	66.7%	22	61.1%
Motor Vehicle and Accessories	22	10	45.5%	9	40.9%
Paper and Board Sector	31	15	48.4%	13	41.9%
Pharmaceutical and Medical Equipment	11	6	45.5%	5	45.5%
Plastics and Rubber	34	15	44.1%	14	41.2%
Textiles and Apparels	28	13	46.4%	12	42.9%
Timber, Wood and Furniture	11	5	45.5%	4	36.4%
Total	340	175	51.5%	151	44.4%

Source: Research Data, 2020

4.2.2 Missing Data

A closer examination of the 175 questionnaires revealed that 24 had more than 15 percent of data missing on key variables of the study. For these T-test were done between missing and non-missing data sets and significant differences were established. In the opinion of Tabachnick and Fidell (2013) one alternative of dealing with missing data is the deletion of the item as long as they are random subsamples of the whole sample. These were therefore deleted from the data set.

Of the remaining 151 questionnaires, 18 had less than 15 percent of data missing on key variables. For these t-tests were also conducted between missing and non-missing data sets and significant differences were not found. Sub-group mean substitution method was used to replace missing values in the data sets (Hair et al., 2014).

4.2.3 Non-Response Sample Bias

An assessment to compare early versus late response sample bias was performed using the Levene's test which was done to ascertain whether the 95 responses representing 62.9 percent received within one month after sending out the questionnaires had an approximately equal variance to those responses representing 37.1 percent received more than one month after sending the questionnaires. Responses received within one month were considered early responses and those received after more than a month were considered as late responses. Table 4.2 below recapitulates the results.

Table 4.2 ***Test for Homogeneity of Variance***

Latent Constructs	Levene's Statistic	Significance Level
Outsourcing	.034	.854
Collaborative Enterprise	.195	.659
Green Strategies	.142	.707
Product Life Cycle Approach	1.311	.254
Information Systems	.005	.946
Resource Deployment	.681	.410
Product Redesign	.200	.655
Process Reengineering	.310	.579
Business Value Chain	.089	.766
Per Unit Variable Cost of Production	1.090	.298
Oder Fill Rate	2.735	.100
Number of Product Lines	.060	.806
Machine Availability	.121	.729
Lead time	.641	.424
Customer Loyalty	1.009	.317
Market Share	.705	.402
Brand Recognition	.343	.559
Waste Reduction	2.178	.142
Revenue Increase	1.279	.260

Source: Research Data, 2020

The null hypothesis in the Levine's test is that there is no difference in the variance of the early responses and the variances of the late responses. If the significance value is > 0.05, Levene's test is non-significant and the assumption of equal variance holds. Table 4.2 shows the significance values to be > 0.05. Although the F-values for the latent construct, product life cycle approach, per unit variable cost of production, customer loyalty, waste reduction and revenue increase are > 1 these remain statistically insignificant. Therefore the Levene's test is non-significant and therefore there is equal variance. This therefore means early and late responses were insignificant statistically.

4.2.4 Duration of Operation in Kenya

Respondents were to inform the study on how long they have been in operation in Kenya. Figure 4.5 below provides a graphical representation of the duration.

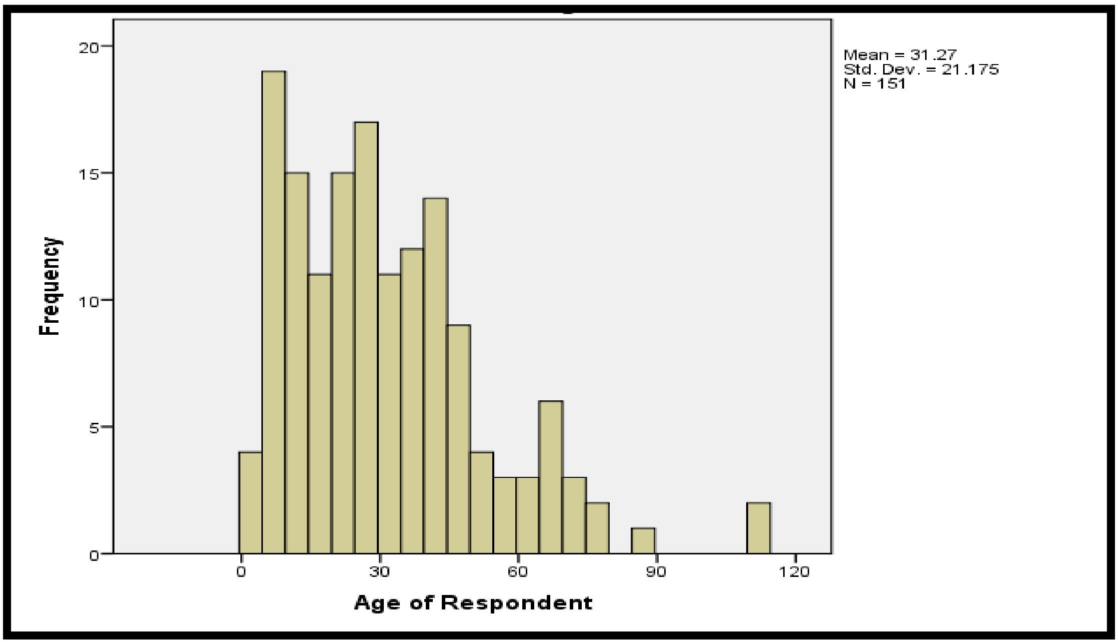


Figure 4.1. **Histogram of the Duration of Operation in Years among Manufacturing Firms**

The distribution in figure 4.1 suggests the greater number of the firms were < 30 years old with the mode standing between 5 and 10 years. These were followed by firms in the age bracket between 30 and 60 years. There were firms older than 60 years with two firms over 100 years old. The table below shows the distribution of the duration of operation in Kenya.

Table 4.3 ***Descriptive Summary for the Duration of Operation among Manufacturing Firms in Kenya***

Description	Statistic Value
Mean	31.27
Standard Deviation (SD)	21.18
Skewness	1.13
Std. Error of Skewness	0.20
Kurtosis	1.71
Std. Error of Kurtosis	0.39
Minimum	2
Maximum	113

Source: Research Data, 2020

Based on table 4.3, the mean age was 31.27 years meaning on average manufacturing firms have been in operation for 31.27 years. The SD was 21.18 years indicating high Coefficient of Variation (CV) of 67.7 percent (21.18/31.27*100 percent). The high co-efficient of variation can be explained by range of ages from 2 years to 113 years. The Z-skewness of 5.65 (1.13/0.20) is > 1.96 meaning that the distribution is positively skewed. Finally the Z-kurtosis value of 4.38 (1.71/0.39) is also > 1.96 showing that the distribution is leptokurtic. The respondents were also asked whether they are ISO 14001 certified or not. ISO 14001 certification indicates the organizations environmental consciousness. Having ISO 14001 was considered a proxy indicator of whether a firm implements reverse logistics. Table 4.4 below recapitulates the responses on ISO 14001 certification.

Table 4.4 ***ISO 14001 Certification Status of Manufacturing Firms***

Class	Frequency	Percent	Cumulative Percent
No	124	82.1	82.1
Yes	27	17.9	100.0

Total	151	100.0

Source: Research Data, 2020

Table 4.4 above reveals that the greater number of manufacturing firms were not ISO 14001 certified. This indicates that the firms need to incorporate more environmental management practices in their processes. The next sub- sections summarizes descriptive statistics for reverse logistics latent variable.

4.2.5: Sampling Adequacy and Sphericity

Sampling adequacy was established using KMO test. According to Kaiser.et.al., (1974) acceptable KMO values should be > 0.70. Bartlett's test of sphericity evaluated whether there is a possibility of dimension reduction. This requires the p-value to be < 0.05. The ensuing sub-sections summarize the results of sampling adequacy and sphericity test for each of the five objectives of the study.

4.2.5.1 Sampling Adequacy and Sphericity Tests for the Association of Reverse Logistics with Competitive Advantage

The first objective of this study was to establish the influence of reverse logistics on competitive advantage. KMO and Bartlett tests were conducted using the latent constructs of reverse logistics and competitive advantage latent variables. Table 4.11 below recapitulates the results of these tests.

Table 4.5 ***Sampling Adequacy and Sphericity Tests for Reverse Logistics Association with Competitive Advantage***

Tests	Co-efficient
Sampling Adequacy Test	0.872
Chi-Square Approximation	2938.359
Degrees of Freedom	36
Significance Level	0.000

Source: Research Data, 2020

Table 4.5 above reveals the KMO test value as 0.872 which is > 0.7. Bartlett's test gave a p-value of 0.000 which is < 0.05. Component matrix values ranged between 0.564 and 0.934. This means that conducting confirmatory factor analysis 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 and competitive advantage as latent variables.

4.2.5.2 Sampling Adequacy and Sphericity Tests for the Association linking Reverse Logistics, Operational Performance and Competitive Advantage

Determining the influence of operational performance on the association linking reverse logistics with competitive advantage was the second objective of the study. KMO and Bartlett tests were applied on the constructs of reverse logistics, operational performance and competitive advantage. Table 4.6 below recapitulates these test results.

Table 4.6 ***Sampling Adequacy and Sphericity Tests for the Association linking Reverse Logistics, Operational Performance and Competitive Advantage***

Test	Co-efficient
Sampling Adequacy Test	0.919
Chi-Square Approximation	4100.481
Degrees of Freedom	91
Significance Level	0.000

Source: Research Data, 2020

Based on table 4.6 the KMO test yielded a value of 0.919 which is > 0.7. Sphericity test gave a p-value of 0.000 which is < 0.05. This means that conducting confirmatory factor analysis 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 operational performance and competitive advantage as latent variables. Component matrix values ranged between -0.09 and 0.937. However the latent construct with a low component matrix co-efficient was per unit variable cost of production. The other latent constructs had component matrix co- efficient < 0.5. This indicates that the latent construct per unit variable cost of production is a potential latent construct to be considered for deletion.

4.2.5.3 Sampling Adequacy and Sphericity Test for the Association linking Reverse Logistics, Process Innovation and Operational Performance

The third objective sought to determine the influence of process innovation on the association linking reverse logistics and operational performance. KMO and Bartlett tests were applied on the constructs of reverse logistics, process innovation and operational performance. Table 4.7 below recapitulates these tests.

Table 4.7 ***Sampling Adequacy and Sphericity Tests the association linking Reverse Logistics, Process Innovation and Operational Performance***

Tests	Co-efficients
Sampling Adequacy Test.	0.950
Chi-Square Approximation	4105.921
Degrees of Freedom	91
Significance Level	0.000

Source: Research Data, 2020

Table 4.7 shows KMO test value of 0.950 which is > 0.7. Sphericity test p-value was 0.000 which is < 0.05. This means that conducting confirmatory factor analysis 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 where reverse logistics, operational performance and competitive advantage are latent variables. The latent construct with low component matrix co-efficient were resource deployment and per unit variable cost of production with co-efficients of - 0.049 and 0.002 respectively indicating they were potential latent constructs to be removed from the model.

4.2.5.4 Sampling Adequacy and Sphericity Test for the Association linking Reverse Logistics, Process Innovation, Operational Performance and Competitive Advantage

The fourth objective sought to examine the conditional indirect effect on the interaction among reverse logistics, process innovation and operational performance on a firm's competitive advantage. Further the fifth objective sought to examine the joint effect of reverse logistics, process innovation and operational performance on a firm's competitive advantage. KMO and Bartlett tests were applied using the constructs of reverse logistics, process innovation, operational performance and competitive advantage. Table 4.8 below recapitulates these test results.

Table 4.8 ***Sampling Adequacy and Sphericity Test for the Association linking Reverse Logistics, Process Innovation, Operational Performance and Competitive Advantage***

Tests	Co-efficients
Sampling Adequacy Test	0.942
Chi-Square Approximation	5927.078
Degrees of Freedom	136
Significance Level	0.000

Source: Research Data, 2020

Based on table 4.8, KMO test results were 0.942 which is > 0.7. Sphericity p-value was 0.000 which is < 0.05. This means that conducting confirmatory factor analysis 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 operational performance and competitive advantage as latent variables. The latent construct with low component matrix co-efficient were resource deployment and per unit variable cost of production with co-efficients of - 0.045 and - 0.008 respectively, indicating they were potential latent constructs to be removed from the model.

4.3 Reliability Tests

Reliability was examined by working out the Cronbach's alpha coefficient at two levels. At the first level coefficients were examined to measure how well the questionnaire items for reverse logistics and process innovation were actually measuring the latent constructs. In the process, questionnaire items that were reducing the internal consistency of the latent construct were deleted. At the second level coefficients were examined to measure how well the latent constructs were actually measuring the latent variable. In both cases a Cronbach alpha coefficient of ≥ 0.7 represented sufficient association among data instruments (Hair et al., 2007). Table 4.9 below provides details of the Cronbach's alpha measuring the internal reliability of the questionnaire items for reverse logistics and process innovation.

Table 4.9 ***Cronbach Alpha Test Results Measuring Internal Reliability of Questionnaire Items for Reverse Logistics and Process Innovation***

	Variables	Cronbach Alpha	Items Deleted
1	Outsourcing	0.708	RLO8
2	Collaborative Enterprise	0.716	CE5, CE6, CE9, CE10
3	Green Strategies	0.729	GS1, GS2, GS3,GS4, GS5, GS14 & GS15
4	Product Life Cycle Approach	0.707	
5	Information Systems	0.704	
6	Resource Deployment	0.744	RD4
7	Product Redesign	0.732	PRD1
8	Process Reengineering	0.723	PRE1, PRE2, PRE3, PRE8, PRE9, PRE12 & PRE13
9	Business Value Chain	0.709	BVA1, BVA2

Source: Research Data, 2020

Based on table 4.9 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 0.704 and 0.744. This indicates sufficient internal consistency between the questionnaire items and the latent constructs they were measuring. Communalities were then assessed using PCA in order to determine how much of the variance in each of the latent constructs for reverse logistics and process innovation were explained by the undeleted questionnaire items (Field, 2013). Pallant (2007) posited that communalities values of less than 0.3 should be dropped because they have low explanatory power. Table 4.10 and 4.11 below summarize the communality coefficient for the questionnaire items measuring the latent constructs for reverse logistics and process innovation respectively.

Table 4.10 ***Communality Coefficient Results for the Questionnaire Items Measuring Reverse Logistics Latent Constructs***

Item Code	Questionnaire Item	Extraction Factor
OS1	Outsourcing reverse logistics increases return on investment	.634
OS2	Outsourcing reverse logistics provides better operational flexibility	.611
OS3	Outsourcing reverse logistics results to improved customer service quality	.440
OS4	Outsourcing reverse logistics results to improved speed to market.	.410
OS5	Reverse logistics outsourcing provides access to functional and industry expertise	.307
OS6	Reverse logistics outsourcing provides access to best technology	.525
OS7	Reverse logistics outsourcing results to benefitting from best practices	.600
CE1	There is high volume data exchange among partners in reverse logistics.	.545
CE2	Partners implementing reverse logistics have standardized information exchange platforms	.432
CE3	The focus in implementing reverse logistics is on building data integrity among supply chain partners	.539
CE4	The emphasis in implementing reverse logistics is on managing transactions using IT tools.	.707
CE7	Supply chain partners have fully integrated reverse logistics processes among themselves	.460
CE8	Supply chain partners have set joint business goals in planning and implementing reverse logistics	.429
GS6	Products are designed to facilitate re-use	.753
GS7	Products are designed to facilitate recycling	.787
GS8	Products are designed to facilitate remanufacture	.612
GS9	Organizational processes optimization leads to a reduction in emissions and solid waste	.723
GS10	Savings in energy and water are an outcome of using technologically cleaner processes	.647
GS11	Recycling of materials internally is practiced during production	.431
GS12	Supply chain partners practice environmental management principles like worker empowerment.	.767
GS13	Environmentally affable packaging such as eco-labeling is used	.889
PLA1	Control and reduction of returns rate does not undermine customer service	.831
PLA2	Supply chain partners segregate returned products into categories for processing, selling or disposal	.779
PLA3	The firm undertakes repair, remanufacture or refurbishing activities to make product reusable	.792
PLA4	The firm recycles returned product parts to be used in manufacture of other products or components	.499
PLA5	The firm undertakes disposal activities for returned products that have no more economic or ecological value	.690
PLA6	The firm facilitates transportation of returned products in the process of recovering value	.663

Source: Research Data, 2020

Based on table 4.10, the communality coefficient for the questionnaire items measuring the latent constructs for reverse logistics range from 0.307 to 0.889. Since these values were > 0.3 it indicates that questionnaire items have sufficient explanatory power on the latent constructs.

Table 4.11 ***Communality Co-efficient Results for the Questionnaire Items Measuring Process Innovation Latent Constructs***

Item Code	Questionnaire Item	Extraction Factor
IS1	Information systems in use are perceived to be better than our competitors.	.826
IS2	Information systems in use are perceived to be better than previous systems.	.765
IS3	Information systems in use are perceived as easy to learn, understand and use.	.771
IS4	Information systems in use are perceived as being compatible to the needs of potential users.	.538
IS5	Users consider information systems as easy to explore and experiment with.	.699
IS6	The results of using the information systems in the organization are visible.	.676
RD1	Firm budgets have a component for reverse logistics activities	.703
RD2	Staff have relevant skills to implement reverse logistics activities	.639
RD3	Supply chain partners have acquired the relevant technology and equipment to implement reverse logistics	.482
RD5	Suppliers are integrated in our current reverse logistics programming	.360
RD6	Resource deployment processes in the firm are perceived to be superior to our competitors	.598
RD7	Over time resource deployment processes in the organization have improved	.541
PRD2	The firm maintains superiority in manufacturing technology	.659
PRD3	Change in customer requirements have influenced our product design strategy	.621
PRD4	Clients consider our current products as more convenient to use	.504
PRD5	Over time manufacturing processes have been standardized and simplified	.754
PRD6	Manufacturing processes are much easier as a result of redesigning our products	.577
PRD7	The benefits of product redesign processes can be quantified within the organization.	.650
PRD8	The quality of our products has improved as a result of product redesign	.686
PRE4	Management constructively use ideas from other staff members	.485
PRE5	Affable interactions among staff exist	.490
PRE6	A teamwork approach is used in problem solving	.530
PRE7	Members of staff work together collegially	.675
PRE10	Employees have a degree of autonomy to make decisions	.449
PRE11	Employee skills updates training programs exist	.385
BVA3	Suppliers have capacity to meet demand variability	.638
BVA4	Suppliers have a fairly constant lead-time variability	.630
BVA5	Suppliers voluntarily share information	.501
BVA6	Suppliers have adequate information and communication sharing infrastructure	.735
BVA7	Clients avail information on demand well in advance	.627
BVA8	Organizational systems have capacity to meet our customers demand variability	.707
BVA9	Customers voluntarily share information	.671

Source: Research Data, 2020

Based on table 4.11, the communality coefficient for the questionnaire items measuring the latent constructs for process innovation range from 0.360 to 0.826, indicating that questionnaire items have sufficient explanatory power on the latent constructs. Table 4.12 below details how well the latent constructs were measuring the latent variables.

Table 4.12 ***Cronbach Alpha Test Results Measuring Internal Consistency of Latent Construct on the Latent Variable***

	Latent variables	Cronbach Alpha	Number of items
1	Reverse Logistics	0.943	4
2	Process Innovation	0.972	4
3	Operational Performance	0.908	4
4	Competitive Advantage	0.897	4

Source: Research Data, 2020

Table 4.12 above the Cronbach alpha coefficient to check whether the latent constructs were actually measuring the latent variables ranged between 0.897 and 0.972. This indicates sufficient internal consistency between the latent constructs and variables they were measuring. Communality assessments using PCA were conducted in order to determine the extent to which the variances in each of the latent variables were explained by the latent constructs. Table 4.13 below details the communality assessment of the latent constructs.

Table 4.13 ***Communality Coefficient Results for the Latent Constructs Measuring Latent Variables***

Latent Variable	Initial	Extraction
Outsourcing	1.000	.938
Collaborative Enterprise	1.000	.914

Green Strategies	1.000	.909
Product Life Cycle Approach	1.000	.898
Information Systems	1.000	.924
Resource Deployment	1.000	.937
Product Redesign	1.000	.937
Process Reengineering	1.000	.855
Business Value Chain	1.000	.968
Per Unit Variable Cost of Production	1.000	.810
Oder Fill Rate	1.000	.832
Number of Product Lines	1.000	.925
Machine Availability	1.000	.894
Lead time Analysis	1.000	.860
Customer Loyalty	1.000	.938
Market Share Analysis	1.000	.915
Brand Recognition Analysis	1.000	.873
Waste Reduction Analysis	1.000	.930
Revenue Increase Analysis	1.000	.941

Source: Research Data, 2020

Based on table 4.13 the communality coefficient for the latent constructs measuring the latent variables for range from 0.810 to 0.968. This means that the latent constructs explained between 81.0 and 96.8 percent of the variance of the respective latent variable. Since these values are > 0.3 it indicates that latent constructs have sufficient explanatory power on the latent variables. The next section discusses tests conducted to establish construct validity of the latent constructs and latent variables.

4.4 Validity Tests

The ensuing sub-sections discuss how content, convergent and discriminant validity tests were conducted and the results thereof.

4.4.1 Content Validity Tests

Content validity evaluated the extent to which conformity existed between the questionnaire items chosen to form a totalized scale and the conceptual interpretation of the latent variable. The objective was to ensure that the selection of questionnaire items explained the latent construct both theoretically and practically. Content validity was checked using a team of resource persons in the field of reverse logistics (Hair et al., 2014).

4.4.2 Convergent and Discriminant Validity

Convergent validity was measured using the standardized factor loading for each of the five objectives of the study. For these the factor loadings were expected to be > 0.5 for acceptable convergent validity. Convergent validity was confirmed through the use of AVE method. For these the AVE for each of the latent constructs is expected to be > 0.5. Discriminant validity which examines how constructs perceived not to be theoretically associated are indeed not associated was measured by comparing the AVE with the MSV. The AVE is expected to be > MSV for the latent variables to be considered not to be theoretically associated. The ensuing sub-sections summarize the results of the convergent and discriminant test per objective.

4.4.2.1 Convergent and Discriminant Validity Tests Associating Reverse Logistics with Competitive Advantage

Establishing the influence of reverse logistics on competitive advantage was the first study objective. Before further statistical analysis convergent and discriminant validity tests were conducted on the latent constructs model depicting the association linking reverse logistics with competitive advantage. Figure 4.2 below shows the standardized factor loadings to check convergent validity on the model depicting the latent constructs and the latent variables of reverse logistics and competitive advantage.

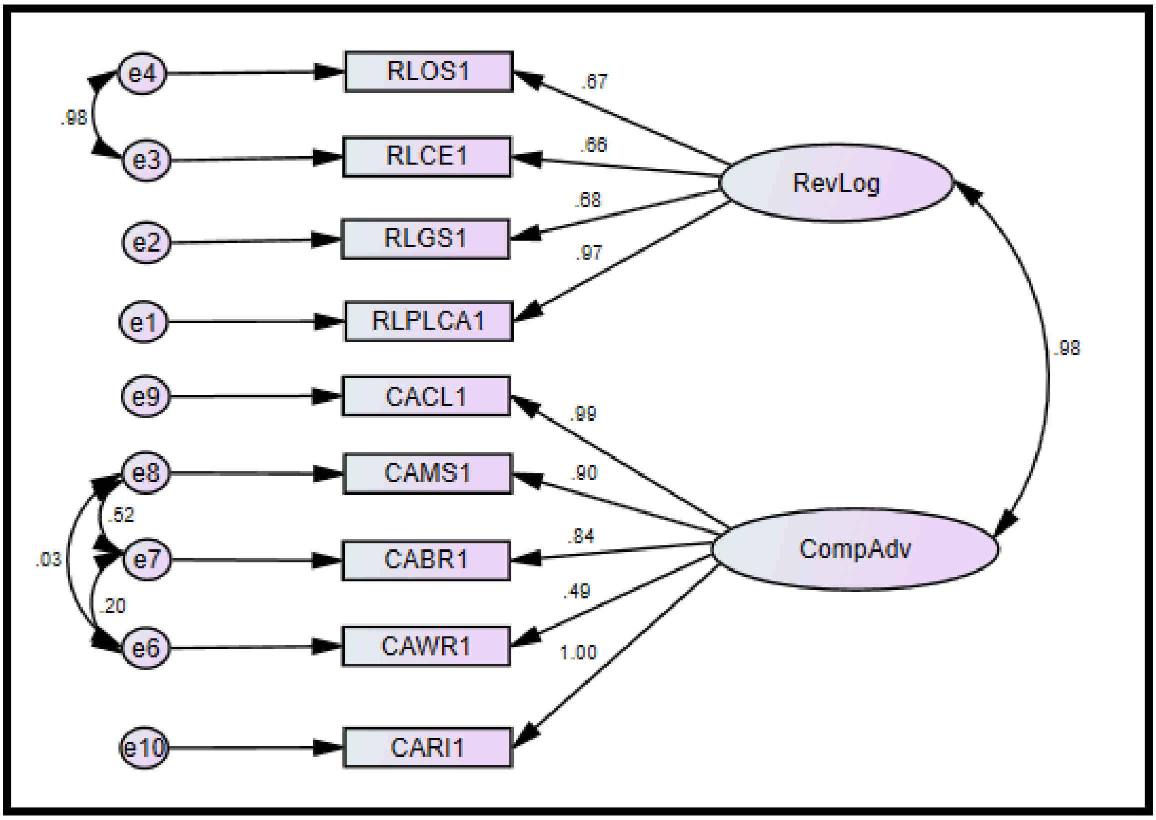


Figure 4.2. **Convergent Validity Test for the Association linking Reverse Logistics with Competitive Advantage**

Based on figure 4.2 above the standardized factor loadings for all the latent constructs of reverse logistics were > 0.5. The standardized factor loadings for each of the latent constructs of competitive advantage were > 0.5 except for the construct CAWR1 with a factor loading of 0.49. This was therefore deleted from the model. These standardized factor loadings suggest that we have acceptable levels of convergent validity. Convergent validity was also checked using AVE. For these the AVE for each of the latent constructs is expected to be > 0.5. Table 4.14 below reveals the AVE for the latent constructs showing the association linking reverse logistics with competitive advantage.

Table 4.14 ***Average Variance Extraction results for Reverse Logistics Interaction with Competitive Advantage***

Factor	<---	Component	Loadings	Squared Loadings	AVE
RLPLCA1	<---	RevLog	0.967	0.935	0.569
RLGS1	<---	RevLog	0.681	0.464	
RLCE1	<---	RevLog	0.658	0.433	
RLOS1	<---	RevLog	0.667	0.445	
CABR1	<---	CompAdv	0.837	0.701	0.875
CAMS1	<---	CompAdv	0.901	0.812	
CACL1	<---	CompAdv	0.992	0.984	
CARI1	<---	CompAdv	1.002	1.004	

Source: Research Data, 2020

Since the AVE values for the association of reverse logistics with competitive advantage are > 0.5, indicating good convergent validity. Discriminant validity which examines how constructs perceived not to be theoretically associated are indeed not associated was measured by comparing the AVE with the MSV. Table 4.15 below summarizes the MSV squared loadings for the reverse logistics association with competitive advantage latent variable.

Table 4.15 ***Maximum Shared Variance results for Reverse Logistics Interaction with Competitive Advantage***

Component	<-->	Component	Loadings	Squared Loadings
RevLog	<-->	CompAdv	0.657	0.431

Source: Research Data, 2020

Based on table 4.15 above the square correlation for the interaction of reverse logistics with competitive advantage latent variables was 0.431. From table 4.14 the AVE for reverse logistics was 0.569. The AVE for competitive advantage latent variable was 0.748. This shows that the square correlation is < the AVE of reverse logistics and competitive advantage latent variables. This suggests discriminant validity among the latent constructs.

4.4.2.2 Convergent and Discriminant Validity among Reverse Logistics, Operational Performance and Competitive Advantage

This study sought to determine the influence of operational performance on the association linking reverse logistics and a firm's competitive advantage as its second objective. Convergent and discriminant validity tests were conducted on the latent constructs model depicting the association among reverse logistics, operational performance and competitive advantage as revealed in figure 4.3 below.

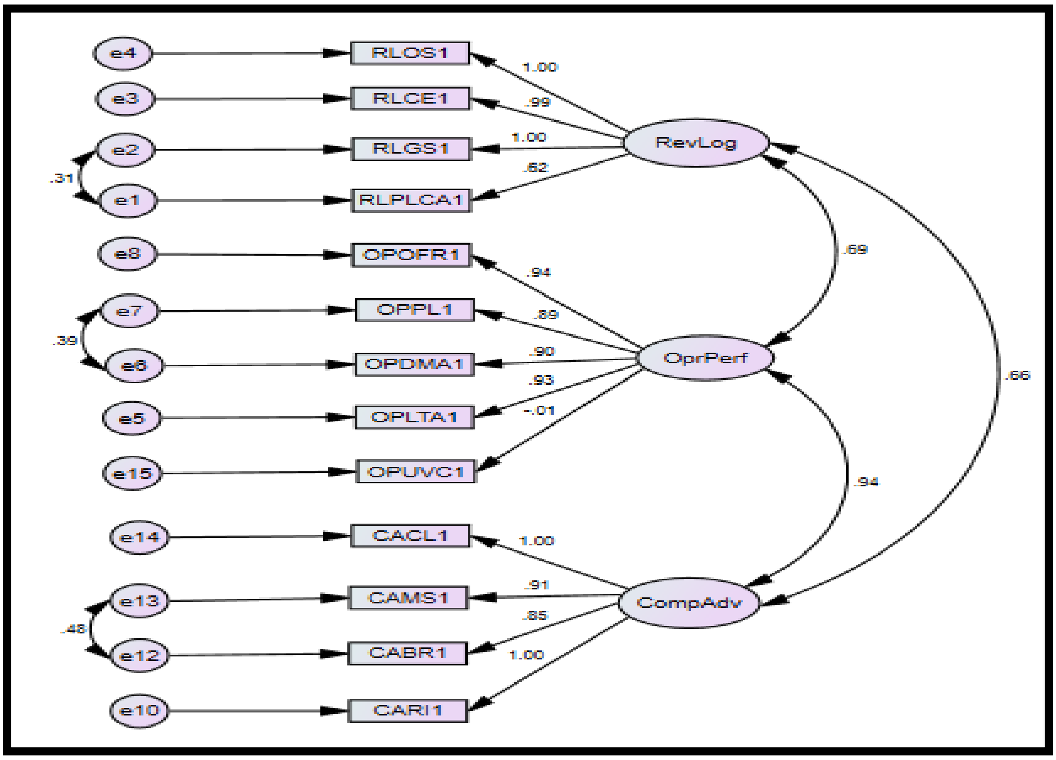


Figure 4.3. **Convergent Validity Test for the Association among Reverse Logistics, Operational Performance and Competitive Advantage**

From figure 4.3, the standardized factor loadings for all the latent constructs of reverse logistics and operational performance were > 0.5 except for the latent construct OPUVC1 which had a standardized factor loading significantly < 0.5. For this reason it was expunged from the model. The standardized factor loadings for all the latent constructs of competitive advantage were > 0.5. The standardized factor loadings establish there was convergent validity. To confirm convergent validity AVE method was used. Table 4.14 below reveals AVE computations.

Table 4.16 ***Average Variance Extraction results for the Association among Reverse Logistics, Operational Performance and Competitive Advantage***

Factor	<---	Component	Loadings	Squared Loadings	AVE
RLPLCA1	<---	RevLog	0.622	0.387	0.841
RLGS1	<---	RevLog	0.997	0.994	
RLCE1	<---	RevLog	0.994	0.988	
RLOS1	<---	RevLog	0.997	0.994	
OPLTA1	<---	OprPerf	0.928	0.861	0.836
OPDMA1	<---	OprPerf	0.903	0.815	
OPPL1	<---	OprPerf	0.888	0.789	
OPOFR1	<---	OprPerf	0.938	0.880	
CARI1	<---	CompAdv	0.998	0.996	0.883
CABR1	<---	CompAdv	0.848	0.719	
CAMS1	<---	CompAdv	0.91	0.828	
CACL1	<---	CompAdv	0.995	0.990	

Source: Research Data, 2020

Since the AVE values for reverse logistics, operational performance and competitive advantage are > 0.5, this indicated good convergent validity. Table 4.17 below summarizes the MSV squared loadings for reverse logistics, operational performance and competitive advantage latent variables to examine discriminant validity.

Table 4.17 ***Maximum Shared Variance results for the Association among Reverse Logistics, Operational Performance and Competitive Advantage***

Component	<-->	Component	Loadings	Squared Loadings
RevLog	<-->	OprPerf	0.691	0.477

RevLog	<-->	CompAdv	0.935	0.874
OprPerf	<-->	CompAdv	0.657	0.432

Source: Research Data, 2020

Based on table 4.17 above the square correlation between reverse logistics and operational performance latent variable was 0.477. This value was < the AVE of reverse logistics latent variable with a coefficient of 0.841 (Table 4.16). The square correlation linking reverse logistics with competitive advantage latent variables was 0.874. This value was not significantly > the AVE of reverse logistics latent variable (Table 4.16). This suggests the latent constructs of reverse logistics were significantly distinct. This means that there was evidence to suggest discriminant validity.

The square correlation between operational performance and reverse logistics latent variables was 0.477. The square correlation between operational performance and competitive advantage latent variables was 0.432. These values were < the AVE of operational performance latent variable with a coefficient of 0.836 (Table 4.16). This means that there was evidence to suggest the constructs of operational performance were unique to the constructs of reverse logistic and those of competitive advantage.

The square correlation between competitive advantage and reverse logistics latent variables was 0.874. This value was not significantly > the AVE of operational performance latent variable with a coefficient of 0.836 (Table 4.16). The square correlation between competitive advantage and operational performance latent variables was 0.432. The value is < the AVE of operational performance latent variable. This means that there was evidence to suggest discriminant validity.

4.4.2.3 Convergent and Discriminant Validity Tests for the Association among Reverse Logistics, Process Innovation and Operational Performance

Determining the influence of process innovation on the association linking reverse logistics and operational performance was the third study objective. Figure 4.4 reveals the standardized factor loadings to check convergent validity on the model depicting the latent constructs and the latent variables of reverse logistics, process innovation and operational performance.

From figure 4.4 below the standardized factor loadings for all the latent constructs for reverse logistics and process innovation were > 0.5 except for PIPRE1 and PIRD1 with a loading of 0.46 an - 0.07 respectively. The latent construct PIRD1 had a loading that was significantly < 0.5. It was therefore expunged from the model. The loadings for each of the latent constructs of operational performance were > 0.5.

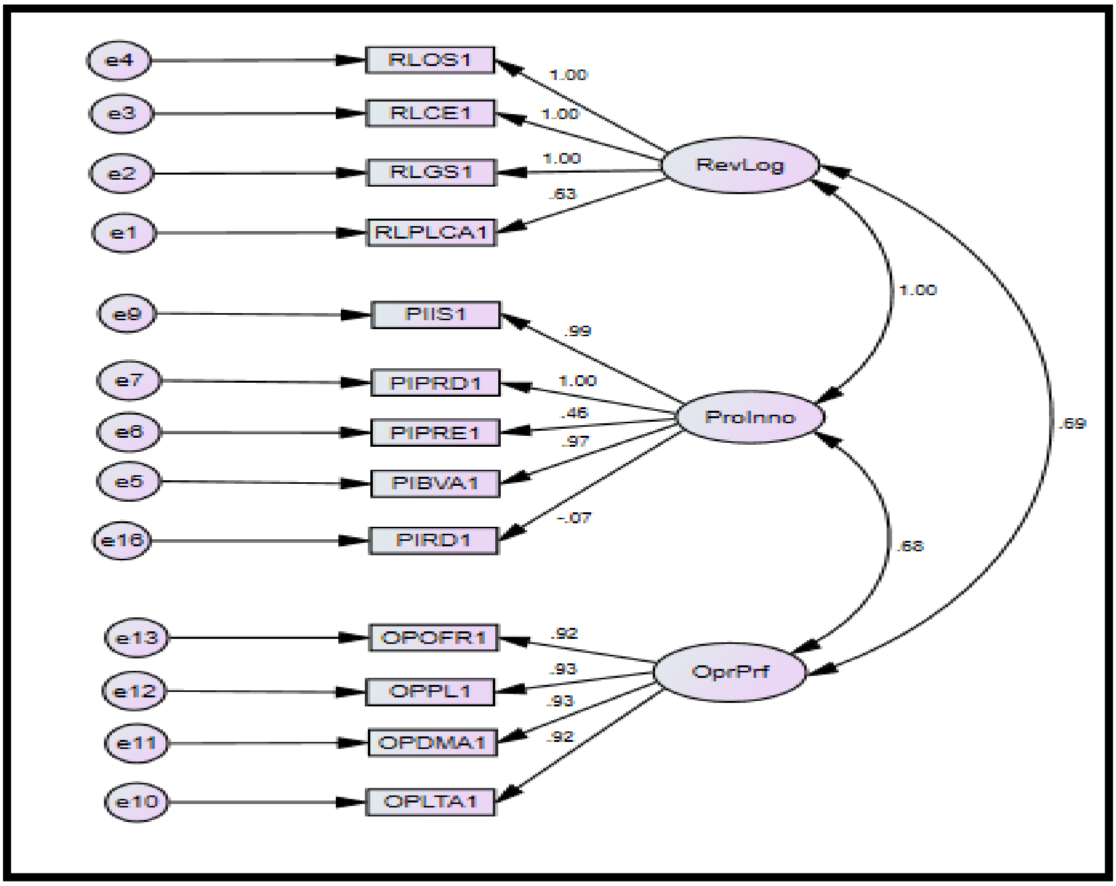


Figure 4.4. **Convergent Validity Test for the Association among Reverse Logistics, Process Innovation and Operational Performance**

To confirm convergent validity AVE method was applied. Table 4.18 below reveals the AVE for the latent constructs for the association among reverse logistics, process innovation and operational performance.

Table 4.18 ***Average Variance Extraction results for the Association among 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	

Source: Research Data, 2020

Since the AVE values for reverse logistics, process innovation and operational performance were > 0.5, this demonstrated good convergent validity among the latent constructs. Table 4.19 below summarizes the MSV squared loadings for reverse logistics, process innovation and operational performance latent variables in measuring discriminant validity.

Table 4.19 ***Maximum Shared Variance results for the Association among Reverse Logistics, Process Innovation and Operational Performance***

Component	**<-->**	Component	Loadings	Squared Loadings
RevLog	<-->	ProInno	0.999	0.998
RevLog	<-->	OprPerf	0.682	0.465
ProInno	<-->	OprPerf	0.690	0.476

Source: Research Data, 2020

Based on table 4.19 above the square correlation between reverse logistics and process innovation latent variables was 0.998. This value was > the AVE of reverse logistics latent variable with a coefficient of 0.844 (Table 4.18). The square correlation between reverse logistics and operational performance latent variables was 0.465. This value was < the AVE of reverse logistics latent variable. This suggests the latent constructs of reverse logistics were not significantly distinct from those of process innovation but they were significantly distinct from those of operational performance. This means that there was evidence to suggest the constructs of reverse logistics were unique from those of operational performance and capture some phenomena that operational performance does not.

The square correlation between process innovation and reverse logistics latent variables was 0.998. This value was > the AVE of process innovation latent variable with a coefficient of 0.782 (Table 4.18). The square correlation between process innovation and operational performance latent variables was 0.476. This value was < the AVE of reverse logistics latent variable. This suggests the latent constructs of process innovation were not significantly distinct from those of reverse logistics but they were significantly distinct from those of operational performance. This means that there was evidence to suggest the constructs of process innovation were unique from those of operational performance.

The square correlation between operational performance and reverse logistics latent variables was 0.465. The square correlation between operational performance and process innovation latent variables was 0.476. These values were < the AVE of operational performance latent variable with a coefficient of 0.845 (Table 4.18). Therefore there was sufficient evidence to suggest the constructs of operational performance were unique and capture some phenomena that reverse logistics and process innovation do not.

4.4.2.4 Convergent and Discriminant Validity Tests for the Association among Reverse Logistics, Process Innovation, Operational Performance and Competitive Advantage

The fourth objective examined the conditional indirect effect on the association linking reverse logistics, process innovation and operational performance on a firm's competitive advantage. The fifth objective examined the joint effect of reverse logistics, process innovation and operational performance on a firm's competitive advantage. Convergent and discriminant validity tests were conducted on the latent constructs model. Figure 4.5 reveals the standardized factor loadings to check convergent validity on the model depicting the latent constructs and the latent variables of reverse logistics, process innovation, operational performance and competitive advantage.

From figure 4.5 below the standardized factor loadings all of the latent constructs for reverse logistics and process innovation were > 0.5 except for the latent construct PIPRE1 with a standardized factor loading of 0.46. Since this was > 0.3 it was not expunged from the model. The loadings for each of the latent constructs of operational performance and competitive advantage were > 0.5.

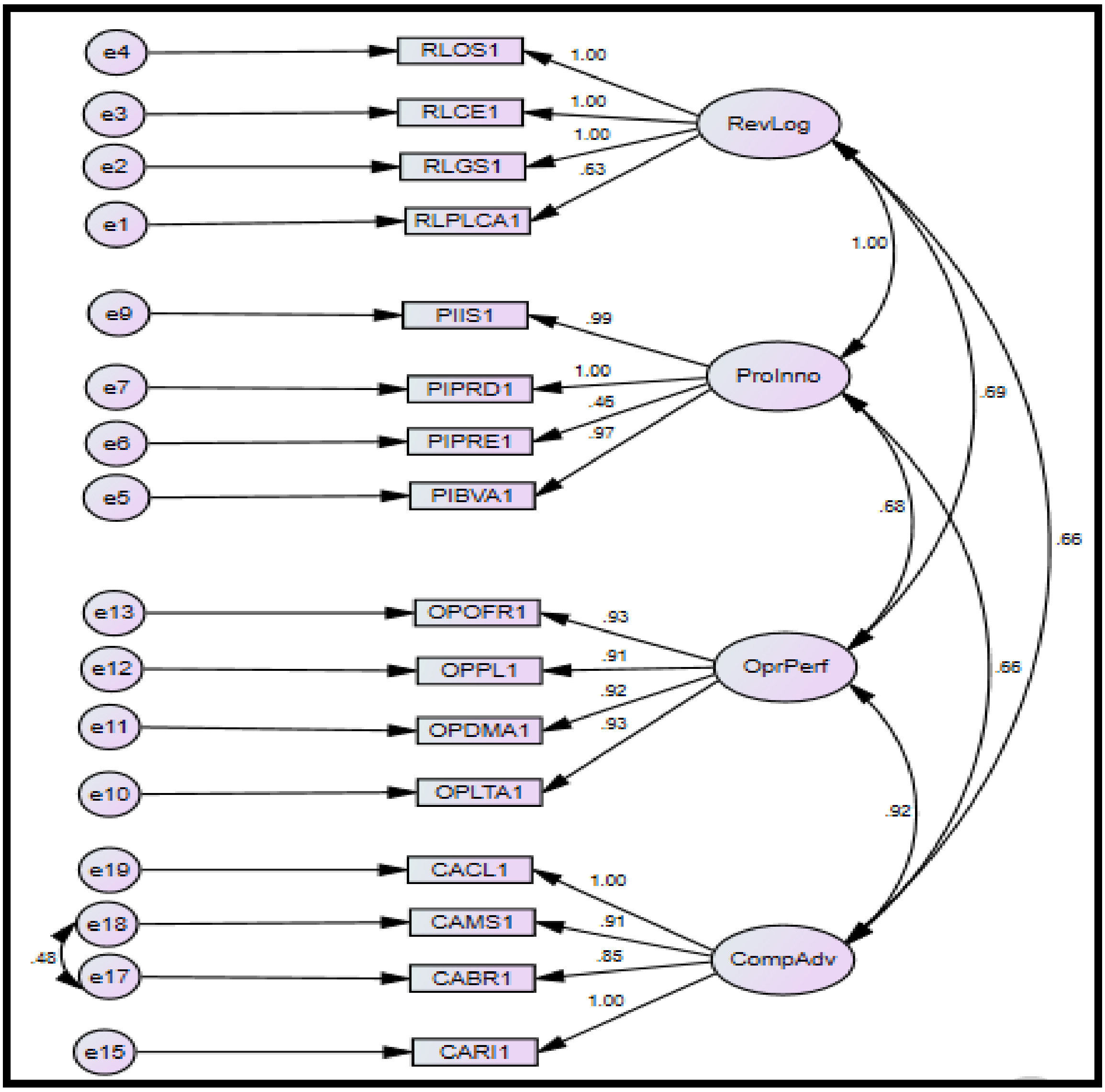


Figure 4.5. **Convergent Validity Test for the Association among Reverse Logistics, Process Innovation, Operational Performance and Competitive Advantage**

Table 4.20 below reveals the AVE for the latent constructs for the association among reverse logistics, process innovation and operational performance to confirm convergent validity.

Table 4.20 ***Average Variance Extraction results for the Association among Reverse Logistics, Process Innovation, Operational Performance and Competitive Advantage***

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	0.928	0.861	0.850
OPDMA1	<---	OprPerf	0.921	0.848	
OPPL1	<---	OprPerf	0.907	0.823	
OPOFR1	<---	OprPerf	0.931	0.867	
CARI1	<---	CompAdv	0.999	0.998	0.883
CABR1	<---	CompAdv	0.848	0.719	
CAMS1	<---	CompAdv	0.909	0.826	
CACL1	<---	CompAdv	0.995	0.990	

Source: Research Data, 2020

Since the AVE values for reverse logistics, process innovation, operational performance and competitive advantage were > 0.5, this demonstrated good convergent validity. Table 4.21 below summarizes the MSV squared loadings for the latent variables to check for discriminant validity.

Table 4.21 ***Maximum Shared Variance results for the Association among Reverse Logistics, Process Innovation and Operational Performance***

Component	<-->	Component	Loadings	Squared Loadings
RevLog	<-->	ProInno	0.999	0.998
RevLog	<-->	OprPerf	0.692	0.479
RevLog	<-->	CompAdv	0.663	0.440
ProInno	<-->	OprPerf	0.684	0.468
ProInno	<-->	CompAdv	0.659	0.434
OprPerf	<-->	CompAdv	0.924	0.854

Source: Research Data, 2020

Based on table 4.21 above the square correlation between reverse logistics and process innovation latent variables was 0.998. This value was > the AVE of reverse logistics latent variable with a coefficient of 0.844 (Table 4.20). The square correlation between reverse logistics and operational performance latent variables was 0.479. The square correlation between reverse logistics and competitive advantage latent variables was 0.440. These values were < the AVE of reverse logistics latent variable. This suggests the latent constructs of reverse logistics were not significantly distinct from latent constructs of process innovation. Further the results suggest the latent constructs of reverse logistics were significantly distinct from the latent constructs of operational performance and competitive advantage. This means that there was evidence to suggest the constructs of reverse logistics were unique from those of operational performance and competitive advantage.

The square correlation between process innovation and reverse logistics latent variables was 0.998. This value was > the AVE of process innovation latent variable with a coefficient of 0.782 (Table 4.20). The square correlation between process innovation and operational performance latent variables is 0.468. This value was < the AVE of process innovation latent variable. The square correlation between process innovation and competitive advantage latent variables is 0.434. This value was < the AVE of reverse logistics latent variable. This suggests the latent constructs of process innovation were not significantly distinct from latent constructs of reverse logistics. Further the results suggest the latent constructs of process innovation were significantly distinct from the latent constructs of operational performance and competitive advantage.

The square correlation between operational performance and reverse logistics latent variables was 0.479. This value was < the AVE of operational performance latent variable with a coefficient of 0.850 (Table 4.20). The square correlation between operational performance and process innovation latent variables was 0.468. This value was < the AVE of operational performance latent variable. The square correlation between operational performance and competitive advantage latent variables was 0.854. This value was > the AVE of operational performance latent variable, although this was not significantly larger. This suggests the latent constructs of operational performance were significantly distinct from latent constructs of reverse logistics and process innovation. Further the results suggest the latent constructs of operational performance were not significantly distinct from the latent constructs of competitive advantage. This means that there was empirical evidence to suggest the constructs of operational performance were unique from those of reverse logistics and process innovation demonstrating discriminant validity.

Finally the square correlation between competitive advantage and reverse logistics latent variables was 0.440. This value was < the AVE of competitive advantage latent variable with a coefficient of 0.883 (Table 4.20). The square correlation between competitive advantage and process innovation latent variables was 0.434. This value was < the AVE of competitive advantage latent variable. The square correlation between competitive advantage and operational performance latent variables was 0.854. This value was > the AVE of competitive advantage latent variable. This suggests the latent constructs of competitive advantage were not significantly distinct from latent constructs of operational performance. Further the results suggest the latent constructs of competitive advantage were significantly distinct from the latent constructs of reverse logistics and process innovation. This means that there was empirical evidence to suggest the constructs of competitive advantage were unique from those of reverse logistics and process innovation.

To further explain the nature of association among the latent constructs of reverse logistics, process innovation, operational performance and competitive advantage, appendix 5, 6, 7, 8, 9 and 10 reveal patterns of correlation among these latent constructs. Appendix 5 indicates the latent constructs of reverse logistics have equal patterns of correlation among themselves in comparison to the correlations between the latent constructs of reverse logistics and process innovation. Similarly, the latent constructs of process innovation have equal patterns of correlation among themselves in comparison to the correlations between the latent constructs of process innovation and reverse logistics. This indicates the interaction among the latent constructs of reverse logistics and process innovation have high association.

Appendix 6 reveals the latent constructs of reverse logistics have higher patterns of correlation among each other compared to patterns of correlation between the latent constructs of reverse logistics and operational performance. Similarly, from appendix 6 and 8 the latent constructs of operational performance have higher patterns of correlation among themselves in comparison to the correlations between the latent constructs of operational performance and reverse logistics and between the latent constructs of operational performance and process innovation. According to appendix 8 the latent constructs of process innovation have higher patterns of correlation among each other compared to patterns of correlation between the latent constructs of process innovation and operational performance. These indicate discriminant validity between the latent constructs of reverse logistics and operational performance and between the latent constructs of process innovation and operational performance.

Appendix 7 reveals the latent constructs of reverse logistics have higher patterns of correlation among each other compared to patterns of correlation between the latent constructs of reverse logistics and competitive advantage. Similarly, from appendix 7 and 9 the latent constructs of competitive advantage have higher patterns of correlation among themselves in comparison to the correlations between the latent constructs of competitive advantage and reverse logistics and between the latent constructs of competitive advantage and process innovation. According to appendix 9 the latent constructs of process innovation have higher patterns of correlation among each other compared to patterns of correlation between the latent constructs of process innovation and competitive advantage. These indicated discriminant validity between the latent constructs of reverse logistics and competitive advantage and between the latent constructs of process innovation and competitive advantage.

Appendix 10 indicated the latent constructs of operational performance have equal patterns of correlation among themselves in comparison to the correlations between the latent constructs of operational performance and competitive advantage. In addition, the latent constructs of competitive advantage have equal patterns of correlation among themselves in comparison to the correlations between the latent constructs of competitive advantage and operational performance. This indicates the interaction between the latent constructs of operational performance and competitive advantage have good discriminant validity.

These validity tests suggest the study had good content and convergent validity. Good discriminant validity especially on the models linking all the latent variables of reverse logistics, process innovation operational performance and competitive advantage was observed. Arguably the models demonstrate good construct validity. The next section discussed the descriptive statistics for all the questionnaire items included in the analysis.

4.5 Reverse Logistics, Process Innovation, Operational Performance and Competitive Advantage Descriptive Statistics

Descriptive statistics were then analyzed to understand the nature of the distributions generated from the questionnaire items. The analysis involved examining the mean, SD, CV, skewness and kurtosis. SD was used to understand variability among items with the same unit of measure while the CV was used to compare levels of variability among items that were not measured on the same measurement scale. The ensuing sub-sections recapitulate the descriptive statistics for reverse logistics, process innovation, operational performance and competitive advantage.

4.5.1 Reverse Logistics

In measuring reverse logistics, four latent constructs namely; outsourcing, collaborative enterprise, green strategies and product life cycle were used. Each of the latent constructs had a number of questionnaire items for which reliability tests were used to check the extent to which they have explanatory power over the construct they were purported to measure. The results are outlined in the ensuing sub-sections.

4.5.1.1 Outsourcing

Outsourcing was measured using seven questionnaire items using a five point Likert scale with 1 being "not at all" and 5 being "to a very large degree". The results are recapitulated in table 4.22. From the table, it can be observed that the mean score for the seven questionnaire items ranged from 3.24 to 3.85 indicating that outsourcing reverse logistics was practiced from a moderate to a large extent. Questionnaire item OS2 had the highest mean score (3.85). This demonstrates that manufacturing firms in Kenya put high emphasis in improving operational flexibility. Questionnaire item OS7 had the lowest mean score (3.24).

Table 4.22 ***Respondent Scores on Outsourcing***

Code	Questionnaire Item	N	Mean	SD	Z-Skewness	Z-Kurtosis
OS1	Outsourcing reverse logistics increases return on investment.	151	3.79	0.64	-3.78	3.04
OS2	Outsourcing reverse logistics provides better operational flexibility.	151	3.85	0.81	-2.48	0.09
OS3	Outsourcing reverse logistics results to improved customer service quality.	151	3.82	0.95	-1.94	-1.97
OS4	Outsourcing reverse logistics results to improved speed to market.	151	3.80	0.93	-1.24	-2.21
OS5	Reverse logistics outsourcing provides access to functional and industry expertise.	151	3.61	0.88	-0.31	-1.77
OS6	Reverse logistics outsourcing provides access to best technology.	151	3.30	0.98	1.97	-2.07
OS7	Reverse logistics outsourcing results to benefitting from best practices.	151	3.24	1.00	1.21	-2.65

Source: Research Data, 2020

The levels of variability in the data set ranged from 0.64 to 1.00 SDs. The questionnaire item OS7 had the highest degree of variability with 1.00 SDs. This means that observations within the item were more scattered away from the mean. The high variability suggests that the respondents were more indifferent in their responses to this item as compared to the other items of measuring reverse logistics outsourcing. The questionnaire item OS1 had the lowest variability in the data set with 0.64 SDs.

The z-skewness statistic ranged from -3.78 to 1.97. Z-skewness scores ranging between ± 1.96 suggest that the distributions were fairly symmetrical. This reveals that observations in the items were fairly equally distributed on either side of the mean. While z-skewness scores that were less than -1.96 suggest that more observations were found on the left side of the mean. Questionnaire item OS1 was most skewed to the left with a z-skewness score of -3.78.

The z-kurtosis statistic ranged from -2.65 to 3.04. Distributions with z-kurtosis scores above 1.96 are considered to be leptokurtic. Z-kurtosis scores ranging between ± 1.96 suggest that the distribution were fairly mesokurtic while those with scores less than -1.96 are considered to be platykurtic. Questionnaire item OS1 had the highest z-kurtosis score of 3.04 meaning that it was leptokurtic. Platykurtic distributions were exhibited by questionnaire items OS7, OS4 and OS6 with z-kurtosis scores of -2.65, -2.21 and -2.07 respectively.

4.5.1.2 Collaborative Enterprising

The respondents indicated the extent to which they engaged in collaborative enterprise in reverse logistics. This was measured using six questionnaire items. Table 4.23 below recapitulates the results for collaborative enterprise latent construct.

Table 4.23 revealed that the mean scores ranged between 3.31 and 3.68 indicating the respondents concurred with the questionnaire items to a moderate extent but tending towards a large extent. The questionnaire item CE1 and CE7 had the highest and lowest mean scores. The degree of variability ranged from 0.82 to 1.13 SDs. The questionnaire item with the highest degree of variability was CE3, while the questionnaire item with the lowest degree of variability was CE1.

Table 4.23 ***Respondents Scores on Collaborative Enterprise***

Code	Questionnaire Item	N	Mean	SD	Z-Skewness	Z-Kurtosis
CE1	There is high volume data exchange among partners in reverse logistics.	151	3.68	0.82	-0.34	-1.40
CE2	Partners implementing reverse logistics have standardized information exchange platforms.	151	3.56	0.90	-0.87	-1.05
CE3	The focus in implementing reverse logistics is on building data integrity among supply chain partners.	151	3.63	1.13	-1.51	-2.52
CE4	The emphasis in implementing reverse logistics is on managing transactions using IT tools.	151	3.50	1.12	-0.61	-2.70
CE7	Supply chain partners have fully integrated reverse logistics processes among themselves.	151	3.31	0.98	0.35	-2.27
CE8	Supply chain partners have set joint business goals in planning and implementing reverse logistics.	151	3.37	0.94	-0.16	-2.45

Source: Research Data, 2020

The z-skewness scores ranged from -1.51 to 0.35. Generally the distributions tended to be skewed to the left because most of them had negative z-skewness scores. For all the questionnaire items the z-skewness values were between ± 1.96 indicating that these distributions were fairly symmetrical. The questionnaire item CE7 had the highest positive z-skewness score and the questionnaire item with the lowest z-skewness score was CE3. The z-kurtosis score ranged from -1.05 to -2.70 with four of the six questionnaire items having z-kurtosis scores below -1.96. This reveals that the distributions were significantly platykurtic. The questionnaire item CE2 had the highest z-kurtosis score and questionnaire item with the lowest z-kurtosis score was CE4.

4.5.1.3 Green Strategies

A set of eight questionnaire items were used to assess green strategies in reverse logistics as recapitulated in table 4.24.

Table 4.24 ***Respondent Scores on Green Strategies***

Code	Questionnaire Item	N	Mean	SD	Z-Skewness	Z-Kurtosis
GS6	Products are designed to facilitate re-use.	151	3.87	0.83	-1.32	-1.45
GS7	Products are designed to facilitate recycling.	151	3.57	0.98	-0.68	-2.45
GS8	Products are designed to facilitate remanufacture.	151	3.48	0.92	0.09	-2.14
GS9	Organizational processes optimization leads to a reduction in emissions and solid waste.	151	3.64	0.84	-1.18	-1.23
GS10	Savings in energy and water are an outcome of using technologically cleaner processes.	151	3.52	0.97	-0.13	-2.41
GS11	Recycling of materials internally is practiced during production.	151	3.48	0.90	-0.18	-1.91
GS12	Supply chain partners practice environmental management principles like worker empowerment.	151	3.53	0.90	-0.94	-1.91
GS13	Environmentally affable packaging such as eco-labeling is used.	151	3.45	0.97	-0.17	-2.38

Source: Research Data, 2020

The results show the mean scores ranged between 3.45 (questionnaire item GS13) and 3.87 (questionnaire item GS6) indicating that the respondents concurred with the questionnaire items moderately but tending towards a large extent. The degree of variability ranged from

0.83 to 0.98 SDs. Questionnaire item GS7 had the highest degree of variability followed by questionnaire item GS10 and GS13. Questionnaire item GS6 had the lowest degree of variability.

The z-skewness scores ranged from -1.32 to 0.09. This generally reflects that all the questionnaire items had fairly symmetrical distributions. The z-kurtosis scores ranged from -2.45 to -1.23. Four of the questionnaire items had z-kurtosis scores below -1.96 suggesting they were platykurtic. The other four questionnaire items had z-kurtosis scores ranging between ±1.96 suggesting they were mesokurtic.

4.5.1.4 Product Life Cycle Approach

Six questionnaire items were used to measure the extent to which firms utilize the product life cycle approach in reverse logistics activities as per table 4.25 below. Based on the table, the mean scores ranged between 3.14 (PLA6) and 3.68 (PLA1). This reveals that respondents concurred with the questionnaire items moderately but tending towards a large extent.

From the ensuing table, variability levels were between 0.87 and 1.04 SDs. Respondents were most inconsistent in their responses to questionnaire item PLA3 and PLA5 respectively. Questionnaire item PLA1 had the lowest degree of variability. The z-skewness scores were between -0.80 and 2.89. Generally reflect that the distributions tended to be symmetrical. The only questionnaire item with a z-skewness score that did not fall in the range ± 1.96 was PLA2. This had a z-skewness value of 2.89 indicating that the distribution was skewed to the right.

Table 4.25 ***Respondent Scores on Product Life Cycle Approach***

Code	Questionnaire Item	N	Mean	SD	Z-Skewness	Z-Kurtosis
PLA1	Control and reduction of returns rate does not undermine customer service.	151	3.68	0.87	-0.29	-1.89
PLA2	Supply chain partners segregate returned products into categories for processing, selling or disposal.	151	3.53	0.89	0.62	-1.85
PLA3	The firm undertakes repair, remanufacture or refurbishing activities to make product reusable.	151	3.63	1.04	-0.14	-2.73
PLA4	The firm recycles returned product parts to be used in manufacture of other products or components.	151	3.65	1.01	-0.80	-2.69
PLA5	The firm undertakes disposal activities for returned products that have no more economic or ecological value.	151	3.43	1.02	1.16	-2.72
PLA6	The firm facilitates transportation of returned products in the process of recovering value.	151	3.14	0.89	2.89	-0.76

Source: Research Data, 2020

The z-kurtosis scores (table 4.25) were between -3.47 to -0.35. Four of the questionnaire items namely; PLA1, PLA2, PLA3 and PLA5 had z-kurtosis scores of less than -1.96 suggesting these distributions formed from the responses of these questionnaire items tended to be platykurtic. The remaining two questionnaire items namely; PLA4 and PLA6 had z-kurtosis values of -1.88 and -0.75. These suggest mesokurtic distributions but tending towards being platykurtic.

4.5.1.5 Summary of Reverse Logistics

Each of the latent constructs forming the reverse logistics variable were aggregated and coefficients that summarize the aggregated data set were calculated. Table 4.26 below provides summarized coefficients of the latent constructs.

Table 4.26 ***Descriptive Summary of Reverse Logistics Latent Constructs***

Latent Construct	N	Mean	Std. Dev	Z-Skewness	Z-Kurtosis
Outsourcing	151	3.63	0.51	0.04	-1.28
Collaborative Enterprise	151	3.51	0.60	0.05	-0.82
Green Strategies	151	3.56	0.44	-0.06	-1.56
Product Life Cycle Approach	151	3.51	0.58	0.11	-0.78

Source: Research Data, 2020

Outsourcing was rated as the most common reverse logistics approach among Kenyan manufacturing firms with a mean of 3.63 (SD = 0.51). The second most common reverse logistics approach was green strategies with a mean of 3.56 (SD = 0.41). The least rated were product life cycle approach and collaborative enterprise both with means of 3.51 (SD = 0.58 and 0.60 respectively). These generally indicate that the respondents generally concurred with the statements moderately but tending towards a large degree.

The z-skewness scores were between -0.06 and 0.11. This generally reflects that the distributions generated from these latent constructs tended to be symmetrical. The z-kurtosis scores were between -1.56 and -0.78. Although this suggests the distributions formed by these latent constructs were mesokurtic but they were tending towards being platykurtic.

The respondents were also asked to provide information regarding reverse logistics cost, level of energy consumption on reverse logistics and the extent to which they undertake refurbishing, remanufacturing, recycling and disposal activities. The ensuing table 4.27 summarizes the responses.

Table 4.27 ***Descriptive Summary of Reverse Logistics Questionnaire Items***

Code	Questionnaire Item	N	Mean	CV (%)	Z-Skewness	Z-Kurtosis
RL1	Estimated cost of running reverse logistics operations in relation to sales.	151	34.52	43.9%	0.34	-1.15
RL2	Estimated cost recovered from reverse logistics activities.	151	34.55	44.2%	0.16	-1.17
RL3	Energy used in handling returns in relation to total energy consumption.	151	29.58	41.8%	-0.01	-0.76
RL4	Rate of product refurbishment in relation to total production.	151	21.06	43.5%	0.34	-0.57
RL5	Rate of product remanufacture in relation to total production.	151	21.01	40.6%	0.40	-0.27
RL6	Raw materials recycled.	151	21.00	41.2%	0.48	-0.07
RL7	Raw materials moved to landfills, incinerated or disposed as waste.	151	20.96	41.7%	0.34	-0.16

Source: Research Data, 2020

Based on table 4.27 above, asked to estimate the percentage of cost of running reverse logistics operations in the manufacturing firm in relation to sales, on average 34.52 percent of cost was spent on running reverse logistics operations among manufacturing firms in Kenya (CV = 43.9 percent). On the questionnaire item requiring firms to estimate costs recovered from reverse logistics activities; on average these firms recovered 34.55 percent of cost from reverse logistics activities (CV = 44.2 percent). Generally this indicates the costs linked to reverse logistics are somewhat equal to the costs recovered from the same. The respondents also indicated that the average amount of energy used in handling returns in relation to total energy consumption was 29.58 percent (CV = 41.8 percent).

The average rate of product refurbishment in relation to total production among the manufacturing firms was 21.06 percent (CV = 43.5 percent). The mean rate of product remanufacture in relation to total production was 21.01 percent (CV = 40.6 percent). The average amount of raw materials recycled was 21.00 percent (CV = 41.2 percent). This indicates that refurbishing, remanufacturing and recycling were undertaken by manufacturing firms with equal measure. The mean amount of raw materials moved to landfills, incinerated or disposed as waste among the manufacturing firms was 20.96 percent (CV = 41.7 percent).

The z-skewness scores ranged between -1.01 and 0.48. These generally reflect that the distributions tended to be symmetrical with a tendency to be skewed to be skewed to the left. The z-kurtosis scores ranged between -1.17 to -0.07. Because these scores were in the range between than ±1.96, it suggests that these distributions formed from the responses of these questionnaire items tended to be mesokurtic but tending towards being platykurtic.

4.5.2 Process Innovation

The latent variable, process innovation was measured using four latent constructs. These were information systems, product redesign, process reengineering and business value chain. The ensuing sub-sections provide descriptive summaries for each of the latent constructs.

4.5.2.1 Information Systems

To measure the extent to which firm utilize information systems to improve process innovativeness, six questionnaire items were used as shown in the ensuing table 4.28. From the table the mean scores ranged between 3.25 (IS6) and 3.99 (IS1, IS2) indicating agreed with the statements moderately and tending towards a large extent.

Table 4.28 ***Respondents Scores on Information Systems***

Code	Questionnaire Item	N	Mean	Std. Dev	Z-Skewness	Z-Kurtosis
IS1	Information systems in use are perceived to be better than our competitors.	151	3.99	0.76	-0.83	-1.92
IS2	Information systems in use are perceived to be better than previous systems in use.	151	3.99	0.83	-0.58	-3.11
IS3	Information systems in use are perceived as easy to learn, understand and use.	151	3.62	0.92	0.34	-2.30
IS4	Information systems in use are perceived as being compatible to the needs of potential users.	151	3.67	0.90	-0.37	-2.03
IS5	Users consider the information systems as easy to explore and experiment with.	151	3.52	0.95	0.83	-2.34
IS6	The results of using the information systems in the organization are visible.	151	3.25	0.93	2.16	-1.57

Source: Research Data, 2020

Variability levels ranged from 0.76 to 0.95 SDs. Respondents were most invariable to questionnaire item IS1. The second most invariable response was questionnaire item IS2. The least invariable response was questionnaire item IS5. The z-skewness scores for the six questionnaire items ranged between -0.83 and 2.16. These generally reflect that the distributions tended to be symmetrical. Questionnaire item IS6 was the only item among the six questionnaire items that the z-skewness score was not within the range ± 1.96. This had a z-skewness value of 2.16 indicating that the distribution was skewed to the right.

The z-kurtosis scores ranged between -3.11 to -1.57. Questionnaire items IS2, IS3, IS4 and IS5 had z-kurtosis scores of less than -1.96 suggesting these distributions formed from the responses of these questionnaire items tended to be platykurtic. Questionnaire items IS1 and IS6 had z-kurtosis values of -1.92 and -1.57 respectively. Although this suggests mesokurtic distributions but they were tending towards being platykurtic.

4.5.2.2 Product Redesign

Product redesign latent construct had a total of seven questionnaire items as indicated in table 4.29. The mean scores ranged between 3.11 and 3.81 showing respondents agreed with the questionnaire items moderately but approaching a large extent. The questionnaire item with the highest score was PRD3 with a mean of 3.81 (SD = 0.82). They also agreed to a large extent with questionnaire item PRD2 with a mean of 3.74 (SD = 0.67). Respondents agreed moderately with questionnaire items PRD7 and PRD8 (Mean = 3.22 and 3.11, SD = 0.93 and 0.94 respectively). Questionnaire item with the highest degree of variability was PRD4 with a mean of 3.72 (SD = 0.97).

The z-skewness scores for the seven questionnaire items ranged between -3.59 and 2.32. Questionnaire items with z-skewness scores of < -1.96 and in ascending order were PRD2 and PRD3 suggesting they are skewed to the left. Questionnaire item with z-skewness scores of > 1.96 was PRD7 suggesting it was skewed to the right. The remaining four questionnaire items had z-skewness scores within the range ± 1.96, indicating they were fairly symmetrical.

Table 4.29 ***Respondent Scores on Product Redesign***

Code	Questionnaire Item	N	Mean	Std. Dev	Z-Skewness	Z-Kurtosis
PRD2	The firm maintains superiority in manufacturing technology.	151	3.74	0.67	-3.59	1.95
PRD3	Change in customer requirements have influenced our product design strategy.	151	3.81	0.82	-2.19	-0.49
PRD4	Clients consider our current products as more convenient to use.	151	3.72	0.97	-1.48	-2.25
PRD5	Over time manufacturing processes have been standardized and simplified.	151	3.68	0.96	-0.86	-2.37
PRD6	Manufacturing processes are much easier as a result of redesigning our products.	151	3.52	0.92	0.05	-2.09
PRD7	The benefits of product redesign processes can be quantified within the organization.	151	3.22	0.93	2.32	-1.42
PRD8	The quality of our products has improved as a result of product redesign.	151	3.11	0.94	1.55	-2.42

Source: Research Data, 2020

The z-kurtosis scores ranged between -2.42 to 1.95. Questionnaire items PRD8, PRD5, PRD4 and PRD6 had z-kurtosis scores < -1.96 and in ascending order. This suggests that these distributions formed from the responses of these questionnaire items tended to be platykurtic. For the other remaining three questionnaire items z-kurtosis scores ranged between ± 1.96, suggesting mesokurtic distributions, although questionnaire item PRD2 was tending towards being leptokurtic.

4.5.2.3 Process Reengineering

Process reengineering latent construct had a total of six questionnaire items. Table 4.30 below indicated that the mean scores ranged between 3.46 and 3.87. The questionnaire item with the highest score was PRE6 with a mean of 3.87 (Std. Dev = 1.02). The questionnaire item with the lowest mean score was PRE11 (Mean = 3.46, SD = 0.90). Questionnaire item PRE7 had the highest SD (Mean = 3.85, SD = 1.07)

Table 4.30 ***Respondent Scores on Process Reengineering***

Code	Process Reengineering	N	Mean	Std. Dev	Z-Skewness	Z-Kurtosis
PRE4	Management constructively use ideas from other staff members.	151	3.71	0.80	-0.22	-1.42
PRE5	Affable interactions among staff exist.	151	3.70	0.80	-0.94	-0.97
PRE6	A teamwork approach is used in problem solving.	151	3.87	1.02	-2.46	-2.30
PRE7	Members of staff work together collegially.	151	3.85	1.07	-2.66	-2.50
PRE10	Employees have a degree of autonomy to make decisions.	151	3.50	0.97	-0.18	-2.47
PRE11	Employee skills updates training programs exist.	151	3.46	0.95	-0.44	-2.36

Source: Research Data, 2020

Based on table 4.30, the six questionnaire items had z-skewness scores ranging between -2.66 and -0.18. Two questionnaire items, PRE7 and PRE6 had z-skewness scores of < -1.96 while the remaining four questionnaire items had ranged between ± 1.96. This suggested that questionnaire item in the process reengineering latent construct were either skewed to the left or fairly symmetrical.

The z-kurtosis scores for the six questionnaire items ranged between -2.50 and -0.97. Four of the questionnaire items PRE7, PRE10, PRE11 and PRE6 had z-kurtosis scores of less than -1.96 indicating that they are platykurtic. The remaining two questionnaire items, PRE4 and PRE5 had z-kurtosis scores ranging between ± 1.96 showing that they are fairly mesokurtic.

4.5.2.4 Business Value Chain

Business value chain latent construct had a total of seven questionnaire items. Table 4.31 below reveals that the means ranged between 2.98 (BVA7) and 3.70 (BVA3), indicating that the respondents concurred with the questionnaire items moderately but approaching a large degree. The questionnaire item with the lowest variability was BVA3 (SD = 0.68). The questionnaire item with the highest variability was BVA7 (SD = 0.88).

Table 4.31 ***Respondent Scores on Business Value Chain***

Code	Questionnaire Item	N	Mean	Std. Dev	Z-Skewness	Z-Kurtosis
BVA3	Suppliers have capacity to meet demand variability.	151	3.70	0.68	-4.06	1.76
BVA4	Suppliers have a fairly constant lead-time variability.	151	3.64	0.89	-1.53	-1.52
BVA5	Suppliers voluntarily share information.	151	3.41	1.05	0.32	-3.02
BVA6	Suppliers have adequate information and communication sharing infrastructure.	151	3.17	0.95	1.81	-2.07
BVA7	Clients avail information on demand well in advance.	151	2.98	0.88	2.68	-1.37
BVA8	Organizational systems have capacity to meet our customers demand variability.	151	3.05	0.85	2.87	-0.40
BVA9	Customers voluntarily share information.	151	3.06	0.88	1.51	-2.19

Source: Research Data, 2020

Based on table 4.31, the seven questionnaire items had z-skewness scores ranging between -4.06 and 2.87. Questionnaire items BVA4, BVA5, BVA9 and BVA6 had z-skewness scores ranging between ± 1.96 indicating they were fairly symmetrical. Questionnaire item BVA3 had z-skewness scores of < -1.96 showing that it was skewed to the left. Questionnaire item BVA7 and BVA8 had z-skewness scores of > 1.96 showing that they were skewed to the right or were positively skewed.

The seven questionnaire items used to measure the business value chain latent construct had z-kurtosis scores ranging from -3.02 to 1.76. Questionnaire items BVA4, BVA7, BVA8 and BVA3 had z-kurtosis scores ranging between ± 1.96 indicating they were fairly mesokurtic. Questionnaire items BVA5, BVA9 and BVA6 had z-kurtosis scores of < -1.96 indicating that they were platykurtic.

4.5.2.5 Summary of Process Innovation

The latent constructs forming the process innovation variable were each aggregated and coefficients that summarize the aggregated data set were then calculated. Table 4.32 below provides a summary of coefficients summarizing latent constructs for process innovation.

Table 4.32 ***Descriptive Summary for Process Innovation Latent Constructs***

Latent Construct	N	Mean	Std. Dev	Z-Skewness	Z-Kurtosis
Information Systems	151	3.67	0.43	-0.03	-0.91
Product Redesign	151	3.54	0.51	-0.06	-1.00
Process Reengineering	151	3.68	0.43	0.32	-0.85
Business Value Chain	151	3.26	0.37	-0.01	-0.96

Source: Research Data, 2020

Based on table 4.32 above, process reengineering and information systems were rated as the most common process innovation approaches with a mean of 3.68 and 3.67 (SD = 0.43 and 0.43 respectively). The least rated was business value chain with an average score of 3.26 (SD = 0.37). These generally indicate that the respondents agreed with the statements from a moderate degree but tending towards a large degree.

The z-skewness scores were between -0.06 and 0.32. This generally reflects that the distributions generated from these latent constructs of process innovation tended to be symmetrical. The z-kurtosis scores were between -1.00 and -0.85. This suggests that the distributions formed by the latent constructs of process innovation were mesokurtic although tending towards being platykurtic.

The respondents were required to share information on the percentage of sales from new products, percentage of budget devoted to research and development, amount of time spent on research and ideation and the percentage of employees trained on innovation. Table 4.33 below provides a summary of the responses.

Table 4.33 ***Descriptive Summary for Process Innovation Questionnaire Items***

Code	Questionnaire Item	N	Mean	CV (%)	Z-Skewness	Z-Kurtosis
PI1	Percentage of sales from new products introduced in the last two years.	151	23.71	45.3%	-0.18	-1.04
PI2	Percentage of budget devoted to research and development.	151	23.41	46.2%	0.22	-1.32
PI3	Percentage of employee hours spent on research and ideation.	151	39.06	45.3%	0.28	-1.10
PI4	Percentage of employees who have received training and tools for innovation.	151	49.55	35.7%	-0.01	-1.01

Source: Research Data, 2020

Based on table 4.33, the percentage of sales from new products introduced in the last two years, was estimated to be 23.71 percent (CV = 45.3 percent). On average 23.41 percent (CV = 46.2 percent) of the budget is devoted to research and development. The amount of employee hours spent on research and ideation averaged 39.06 percent (CV = 45.3 percent). The percentage of employees who had received training and tools for innovation averaged 49.55 percent (CV = 35.7 percent).

The z-skewness scores ranged between -0.18 and 0.28. These reflect symmetry in the distributions. The z-kurtosis scores ranged between -1.32 to -1.01. Because these scores were in the range between than ±1.96, it suggests that these distributions formed from the responses of these questionnaire items tended to be mesokurtic but tending towards being platykurtic.

4.5.3 Operational Performance

Operational performance was measured using four constructs namely; quality, flexibility, dependability and delivery speed. In order to measure quality, order fill rate was used. Flexibility was measured using the number of product lines. Dependability was measured using capacity utilization rate of machine and equipment as a proxy indicator. Delivery speed was measured using lead-time. Table 4.34 below provides recapitulated descriptive statistics for the four constructs.

Table 4.34 ***Descriptive Statistics for Operational Performance***

Operational Performance	N	Mean	CV (%)	Z-Skewness	Z-Kurtosis
Oder Fill Rate	151	95.20	2.0%	0.26	-1.32
Number of Product Lines	151	9.47	36.6%	0.06	-0.74
Machine Availability	151	91.26	1.3%	0.33	-1.33
Lead time Analysis	151	10.50	33.7%	0.01	-1.00

Source: Research Data, 2020

Based on the table 4.34 above, using the order fill rate, on average the number of items actually delivered to customers in the course of the year stated as a percentage of the total orders stood at 95.20 percent (CV = 2.0 percent). The average number of product-lines among manufacturing firms was 9.47 (CV = 36.6 percent). Using the capacity utilization rate, on average the number of hours of equipment/machines that were actually available for manufacturing operations in the year stated as a percentage of the hours these equipment/machines are supposed to be available for manufacturing operations was 91.26 percent (CV = 1.3 percent). An analysis of the lead-time revealed the mean number of days between order receipt and shipment to the customer was 10.50 days (CV = 33.7 percent).

The four constructs used to measure operational performance had z-skewness scores ranging between 0.01 and 0.33. These scores ranged between ± 1.96 indicating they were fairly symmetrical. Z-kurtosis scores ranged from - 1.33 to - 0.74. These z-kurtosis scores range between ± 1.96 indicating that the distributions were mesokurtic.

4.5.4 Competitive Advantage

Competitive advantage was measured using five constructs namely; customer loyalty, market share, brand recognition, waste reduction and revenue increase. Customer loyalty was measured using the customer retention rate. Market share was measured using the market share index for each firm in each industry. Brand recognition was measured using the profit margin as a proxy indicator. Waste reduction was measured using the non-defective rate. Revenue increase was measured by subtracting the revenue for last from those of the previous year and dividing this with the revenue for the previous year to determine the percentage increase. Table 4.35 below provides recapitulates descriptive statistics for the five constructs.

Table 4.35 ***Descriptive Statistics for Competitive Advantage***

Competitive Advantage	N	Mean	CV (%)	Z-Skewness	Z-Kurtosis
Customer Loyalty	151	91.66	3.2%	0.01	-1.58
Market Share	151	17.52	20.6%	-0.07	-1.40
Brand Recognition	151	26.97	25.7%	-0.19	-1.89
Revenue Increase	151	6.43	31.6%	-0.23	-1.32

Source: Research Data, 2020

Based on table 4.35 above, on average the customer retention rate was 91.66 percent (CV = 3.2 percent). The mean market share for the manufacturing firms was 17.52 percent (CV = 20.6 percent). On average the profit margin for the manufacturing firms was 26.97 percent (CV = 25.7 percent) and the average revenue increase for the manufacturing firms was 6.43 percent (CV = 31.6 percent).

The four constructs used to measure competitive advantage had z-skewness scores ranging between -0.23 and 0.01 indicating symmetrical distributions. Z-kurtosis scores ranged from -1.89 to -1.32. These z-kurtosis scores range between ± 1.96 indicating that the distributions are mesokurtic but tended towards being platykurtic.

4.6 Data Diagnostics

The diagnostic tests were essential in checking the integrity of the data before conducting further statistical analysis. This section focused on conducting outlier, normality, autocorrelation, linearity, multicolinearity and heteroscedasticity test. CFA to check on the overall model fitness was conducted per objective and the results presented in this section. The sub-sections below discuss each of these tests in detail.

4.6.1 Outlier Tests

Outliers were examined using a univariate identification method. Each observation was then tested to see the extent to which its SD was significantly different from the mean. In the opinion of Hair et al. (2014) outliers are identified as those observations with standard scores > 2.5 or < -2.5. Table 4.36 below summarizes the ranges for each variable by checking the minimum and maximum standard scores.

Table 4.36 ***Test for Outliers***

	Latent Constructs	Outlier Test Ranges	
		Minimum	Maximum
1	Outsourcing	-2.120	2.104
2	Collaborative Enterprise	-2.153	2.058
3	Green Strategies	-2.194	2.157
4	Product Life Cycle Approach	-2.108	2.145
5	Information Systems	-2.096	2.124
6	Product Redesign	-2.221	2.195
7	Process Reengineering	-2.421	2.301
8	Business Value Chain	-2.105	2.107
9	Oder Fill Rate	-1.989	2.112
10	Number of Product Lines	-2.153	2.170
11	Machine Availability	-2.059	2.277
12	Lead time Analysis	-2.121	2.123
13	Customer Loyalty	-2.005	2.019
14	Market Share Analysis	-2.085	2.072
15	Brand Recognition Analysis	-2.056	1.947
16	Revenue Increase Analysis	-2.145	2.132

Source: Research Data, 2020

Based on table 4.36 the lowest minimum standard score for all variables was -2.421 while the highest maximum standard score was 2.301. This indicates that for all observations within every variable value were within the ± 2.5 standard score criteria. This reveals that the data set did not have outliers.

4.6.2 Normality Tests

Kolmogorov-Smirnov test and Shapiro-Wilk test were used for testing of normality (Field, 2013). Both tests require the p-value to be > 0.05 in order to have ample evidence to presume that the distribution is normally distributed. Table 4.37 provides the statistic and significance level for each of the constructs in the study for the two normality tests.

Table 4.37 ***Kolmogorov-Smirnov and Shapiro-Wilk Test Results***

	Variable	Kolmogorov-Smirnov[a]		Shapiro-Wilk	
		Statistic	Sig.	Statistic	Sig.
1	Outsourcing	.071	.058	.984	.073
2	Collaborative Enterprise	.065	.200*	.986	.141
3	Green Strategies	.060	.200*	.984	.069
4	Product Life Cycle Approach	.064	.200*	.987	.184
5	Information Systems	.070	.058	.984	.073
6	Product Redesign	.065	.200*	.984	.078
7	Process Reengineering	.069	.059	.983	.062
8	Business Value Chain	.070	.061	.984	.069
9	Oder Fill Rate	.046	.200*	.985	.093
10	Number of Product Lines	.069	.079	.984	.079
11	Machine Availability	.039	.200*	.990	.348
12	Lead time Analysis	.067	.098	.984	.069
13	Customer Loyalty	.035	.200*	.985	.109
14	Market Share Analysis	.055	.200*	.983	.052
15	Brand Recognition Analysis	.044	.200*	.983	.063
16	Revenue Increase Analysis	.033	.200*	.987	.190

Source: Research Data, 2020

The results of the Kolmogorov-Smirnov for all the 16 key variables of the study show significance levels with the lowest at 0.058 and the highest > 0.200. While the Shapiro-Wilk test results for all the 16 key variables show significance levels ranging from 0.069 to 0.348. Since the p-values are > 0.05 we presume that the distributions generated by the observations for each variable have a normal distribution.

4.6.3 Tests for Autocorrelation

Durbin-Watson test statistic (D) was used to test for autocorrelation of the first order. According to Gujarati (2003) Durbin-Watson test statistic criteria is dependent on the number of observations of the predictor variables entered and the number of predictor variables. For this study the number of observations was 151 while the number of independent variables entered was 4. From the Durbin-Watson test statistic table for 151 observations at 4 degrees of freedom the acceptance region was the range between 1.788 and 2.212. The regions of indecision are between 1.679 and 1.788 and between 2.212 and 2.321. Durbin-Watson statistics that fall in the indecision range were going to be further tested using the modified Durbin-Watson statistic. Table 4.38 reveals the calculated Durbin-Watson statistic value for each dependent variable among the study variables with the associated independent variables entered.

Results in table 4.38 reveal that where reverse logistics latent constructs were entered as independent variables against the respective operational performance and competitive advantage latent constructs as dependent variables the Durbin-Watson calculated statistics values ranged from 1.848 to 2.148. These were all within the acceptance region of 1.788 to 2.212 meaning that serial autocorrelation does not exist at the first order level.

Table 4.38 ***Durbin-Watson Test Statistic***

Independent Variables Entered	Dependent Variable	Durbin – Watson Statistic
Outsourcing	Customer Loyalty	1.848
Collaborative Enterprise	Market Share	1.878
Green Strategies	Brand Recognition	1.949
Product Life Cycle Approach	Revenue Increase	1.880
	Order Fill Rate	2.002
	Number of Product Lines	2.110
	Machine Availability	1.923
	Lead-time	2.148
Information Systems	Customer Loyalty	2.010
Product Redesign	Market Share	2.088
Process Reengineering	Brand Recognition	1.972
Business Value Chain	Revenue Increase	2.099
	Order Fill Rate	2.093
	Number of Product Lines	1.859
	Machine Availability	1.808
	Lead-time	2.138
Oder Fill Rate	Customer Loyalty	1.989
Number of Product Lines	Market Share	2.000
Machine Availability	Brand Recognition	2.033
Lead-time	Revenue Increase	2.028

Source: Research Data, 2020

Further the results reveal that where process innovation latent constructs were entered as independent variables against the respective operational performance and competitive advantage latent constructs as dependent variables the Durbin-Watson calculated statistics values ranged from 1.808 to 2.138. These latent constructs had Durbin-Watson statistics within the acceptance region meaning that serial autocorrelation does not exist at the first order level.

Finally the results reveal that where the operational performance latent constructs were entered as independent variables against the respective competitive advantage latent constructs as dependent variables the Durbin-Watson calculated statistics values ranged from 1.989 to 2.033. These latent constructs had Durbin-Watson statistics within the acceptance region meaning that serial autocorrelation does not exist at the first order level.

4.6.4 Linearity Test

Linearity tests were conducted by obtaining bivariate correlations among the latent constructs of the latent variables of reverse logistics, process innovation operational performance and competitive advantage were calculated and the p-values examined at 0.05 significance level. The p-values were expected to be < 0.05. Appendix 5, 6, 7, 8, 9 and 10 reveal the results of these bivariate correlations.

Appendix 5 reveals the bivariate correlations between the latent constructs of reverse logistics and process innovation and their significance levels. From appendix 6 all the bivariate correlations were significant at ά = 0.01. This indicates linearity among the latent constructs of reverse logistics and process innovation. Correlation co-efficients ranged from 0.440 to 0.994 indicating moderate to very strong positive correlation among the latent constructs

Appendix 6 reveals the bivariate correlations between the latent constructs of reverse logistics and operational performance and their significance levels. From appendix 6 the bivariate correlations were significant at ά = 0.01. This indicates linearity among the latent constructs of reverse logistics and operational performance. Correlation co-efficients ranged between 0.564 and 0.994 indicating moderate to very strong positive correlation among the latent constructs

Appendix 7 reveals the bivariate correlations among the latent constructs of reverse logisitics and competitive advantage were significant at ά = 0.01. This indicates linearity among the latent constructs of reverse logistics and competitive advantage. Correlation co-efficients ranged between 0.613 to 0.994 indicating weak to very strong positive correlation.

Appendix 8 and 9 reveals that the bivariate correlations between the latent constructs of process innovation and operational performance and between process innovation and competitive advantage were significant at ά = 0.01. This indicates linearity among the latent constructs of process innovation and operational performance and among latent constructs of process innovation and competitive advantage. Correlation co-efficients of the latent constructs of process innovation and operational performance ranged between 0.448 and 0.989 indicating moderate to very strong positive correlation. Correlation co-efficients of the latent constructs of process innovation and competitive advantage ranged between 0.448 and 0.989 indicating weak to very strong positive correlation.

Appendix 10 reveals that the bivariate correlations between the latent constructs of operational performance and competitive advantage were significant at ά = 0.01. This indicates linearity among the latent constructs of operational performance and competitive advantage. Correlation co-efficients ranged between 0.793 to 0.927 indicating moderate to very strong positive correlation. Arguably there was linearity among the latent constructs of reverse logistics, process innovation, operational performance and competitive advantage. The next sub-section tests the latent constructs for multicollinearity.

4.6.5 Multicollinearity Test

VIF was used to diagnose collinearity where the VIF for the independent latent constructs were expected to be < 10 if the variable is not collinearly related to the other regressor variables (Tabachnick & Fidell, 2013). Multicollenearity tests are recapitulated in table 4.39.

Table 4.39 ***Multicollinearity Test Statistic***

Independent Latent Constructs Entered		Multicollinearity Test	
		Tolerance	Variable Inflation Factor (VIF)
1	Outsourcing	0.894	1.119
2	Collaborative Enterprise	0.924	1.082
3	Green Strategies	0.954	1.048
4	Product Life Cycle Approach	0.194	5.148
5	Information Systems	0.179	5.597
6	Product Redesign	0.197	5.075
7	Process Reengineering	0.351	2.849
8	Business Value Chain	0.596	1.679
9	Oder Fill Rate	0.160	6.267
10	Number of Product Lines	0.164	6.114
11	Machine Availability	0.139	7.178
12	Lead time Analysis	0.177	5.659

Source: Research Data, 2020

In table 4.39 above, the VIF values for the latent constructs of reverse logistics and operational performance were between 1.082 and 7.178. The corresponding tolerance values ranged between 0.139 to 0.954. Since all the VIF co-efficients were < 10, they indicated the latent constructs were not multicollinearly associated.

4.6.6 Heteroscedasticity Test

Heteroscedasticity was tested using the Koenker test. For this tests if the p-value is > 0.05 then heteroscedasticity is not present and homoscedasticity is assumed (Hair et al., 2014).

Table 4.40 ***Koenker Test Results***

Independent Variables Entered	Dependent Variable	Koenker Test p-values
Outsourcing	Customer Loyalty	0.348
Collaborative Enterprise	Market Share	0.062
Green Strategies	Brand Recognition	0.071
Product Life Cycle Approach	Revenue Increase	0.356
	Order Fill Rate	0.494
	Number of Product Lines	0.329
	Machine Availability	0.082
	Leadtime Analysis	0.101
Information Systems	Customer Loyalty	0.142
Product Redesign	Market Share	0.867
Process Reengineering	Brand Recognition	0.183
Business Value Chain	Revenue Increase	0.159
	Order Fill Rate	0.055
	Number of Product Lines	0.512
	Machine Availability	0.509
	Leadtime Analysis	0.702
Oder Fill Rate	Customer Loyalty	0.073
Number of Product Lines	Market Share	0.216
Machine Availability	Brand Recognition	0.197
Lead time Analysis	Revenue Increase	0.316

Source: Research Data, 2020

From table 4.40 above, reverse logistics latent constructs were tested for heteroscedasticity as independent variables against the respective competitive advantage and operational performance latent constructs as dependent variables. The Koenker calculated test statistics value ranged from 0.062 to 0.494. Because these p-values are > 0.05 then the variance of the outcome variable given predictor variables is presumed to be constant and therefore homoscedasticity is assumed.

Further the process innovation latent constructs were tested for heteroscedasticity as independent variables against the respective competitive advantage and operational performance latent constructs as dependent variables. The Koenker test calculated statistics value ranged from 0.055 to 0.702. Since these p-values are > 0.05 then the variance of the dependent variables given the independent variables is presumed to be constant and therefore there is no heteroscedasticity.

Finally the operational performance latent constructs were tested for heteroscedasticity as independent variables against the respective competitive advantage latent constructs as dependent variables. The Koenker test calculated statistics value ranged from 0.073 to 0.316. Since these p-values are > 0.05 then the variance of the dependent variables given the independent variables is presumed to be constant and therefore there is no heteroscedasticity.

4.6.7 Confirmatory Factor Analysis

To assess both the overall fitness of the SEM model and the statistical significance of measured model and the structured model an evaluation of the standardized factor loadings was done. This was done for each of the five objectives of the study. The ensuing sub-sections summarize the results of the CFA for the measured model and of the structured models for the five objectives.

4.6.7.1 Confirmatory Factor Analysis for the Measured Model for the Latent constructs

The overall model fit of the measured models was assessed through the absolute, incremental and parsimonious model fitness tests. Absolute fitness was assessed using chi-square value, p-value, RMSEA and GFI where the chi-square value was expected to be small, p-value > 0.05, RMSEA < 0.80 and GFI > 0.90. Incremental model fitness was assessed using AGFI, CFI, NFI and TLI. For a good incremental fit, AGFI > 0.90, CFI >

0.90, 0.8 < NFI < 1.00 and TLI > 0.9. Parsimonious model fitness was assessed using CMIN/DF. For a good parsimonious fit the minimum discrepancy ratio is expected to be < 5. Table 4.41 below summarizes the results of the CFA for the measured model for the latent constructs of reverse logistics, process innovation, operational performance and competitive advantage.

Table 4.41 ***Overall Model Fit Results for the Latent Constructs of Reverse Logistics Process Innovation, Operational Performance and Competitive Advantage***

Test	Decision Criteria	Model Result			
		RevLog	ProInno	OprPerf	CompAdv
Chi-Square		0.319	0.253	5.050	0.122
Degrees of Freedom		1	2	2	1
p-value	> 0.05	0.572	0.881	0.080	0.727
GFI	> 0.90	0.999	0.999	0.983	1.000
CFI	> 0.90	1.000	1.000	0.995	1.000
AGFI	> 0.90	0.989	0.996	0.916	0.996
NFI	0.8 < NFI < 1.00	1.000	1.000	0.993	1.000
TLI	> 0.90	1.003	1.005	0.986	1.005
RMSEA	< 0.08	0.000	0.000	0.101	0.000
CMIN/DF	< 5	0.319	0.126	2.525	0.122

Source: Research Data, 2020

From the results absolute fitness was assessed using chi-square value, p-value, RMSEA and GFI where the chi-square value ranged between 5.050 and 0.122 indicating they were small. P-value ranged between 0.08 and 0.881 showing that they were > 0.05. RMSEA < values for the latent constructs of reverse logistics, process innovation and competitive advatange were > 0.08. The RMSEA value for the latent constructs of operational performance was 0.101 which was not significantly > 0.08. GFI values ranged between 0.983 and 1.000 indicating they were > 0.90. These suggest that the measured models had good absolute fit.

Incremental model fitness was assessed using AGFI, CFI, NFI and TLI. AGFI values ranged between 0.916 and 0.996. These were all > 0.90. CFI values were between 0.995 and 1.000 indicating they were all > 0.90. The NFI values ranged between 0.993 and 1.000 showing they were between the threshold values, 0.8 < NFI < 1.00. TLI values were ranging between 0.986 and 1.005 showing they were > 0.9. These values indicate that all the measured models for the latent constructs had good incremental fit. CMIN/DF values ranged between 0.122 and 2.525. The minimum discrepancy ratio was expected to be < 5. These indicated that measured models for the latent constructs had good parsimonious fit.

4.6.7.2 Confirmatory Factor Analysis for the Association linking Reverse Logistics with Competitive Advantage

Establishing the influence of reverse logistics on competitive advantage was the first objective of the study. CFA was using chi-square value, RMSEA, GFI, AGFI, CFI, NFI, TLI and CMIN/DF. Table 4.49 below summarizes the results of the CFA for the interaction of reverse logistics with competitive advantage.

Table 4.42 ***Overall Model Fit results for the Association linking Reverse Logistics with Competitive Advantage***

Test	Decision Criteria	Model Result
Chi-Square		49.099
Degrees of Freedom		16
GFI	> 0.90	0.929
CFI	> 0.90	0.989
AGFI	> 0.90	0.841
NFI	0.8 < NFI < 1.00	0.983
TLI	> 0.90	0.980
RMSEA	< 0.80	0.117
CMIN/DF	< 5	3.069

Source: Research Data, 2020

Table 4.42 above reveals chi-square value as 49.099 which was considered to be fairly small given that the number of degrees of freedom is 16. RMSEA was 0.117 which is > 0.08 but not significantly larger. The GFI of 0.929 was > 0.90. These suggest that the model had a fairly good absolute fit.

From table 4.42 above, AGFI, CFI, NFI and TLI had coefficients of 0.841, 0.989, 0.983 and 0.980. NFI was within the range between 0.80 and 1.00. CFI and TLI were > 0.9. Although the AGFI was low (0.841) it was tending towards the threshold of 0.9. These indicate the model had a fairly good incremental fit. Table 4.42 indicated a CMIN/DF of 3.069 which was < 5 suggesting a good parsimonious fit. Generally the model had good overall fit. Figure 4.6 below reveals the unstandardized structural equation model for the reverse logistics interaction with competitive advantage.

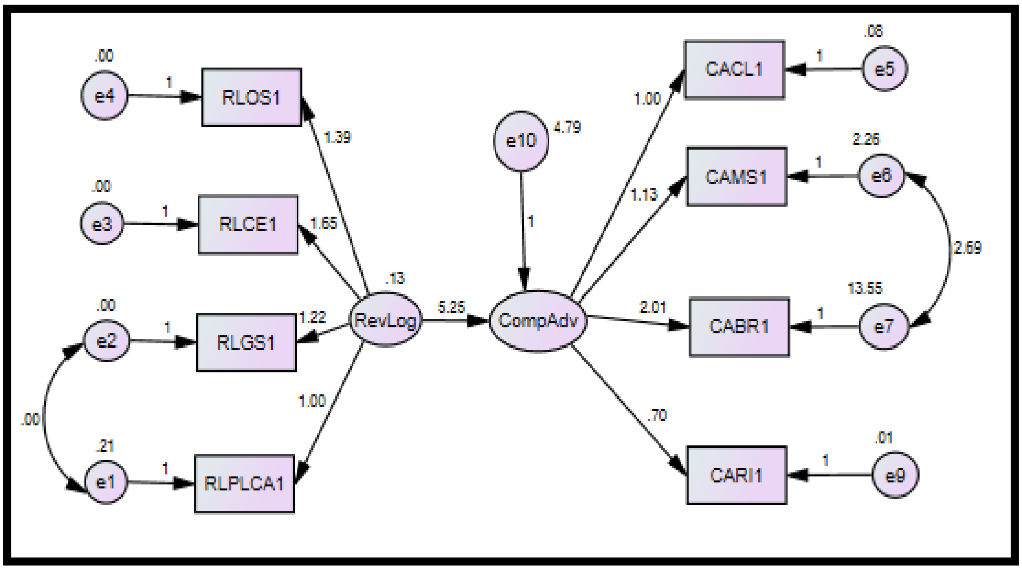


***Figure 4.6.* Unstandardized Structural Equation Model for the Reverse Logistics Interaction with Competitive Advantage.**

An assessment of whether the unstandardized factor loadings were statistically significant was then performed by calculating the standard error of the estimates, the critical ration and p-values as revealed in table 4.43 below.

Table 4.43 ***Unstandardized Factor Loadings for the Measured Model of Reverse Logistics Interaction with Competitive Advantage***

Factor	<---	Component	Estimate	Standard Error	Critical Ratio	p-value
RLCE1	<---	RevLog	1.000			
RLGS1	<---	RevLog	0.739	0.008	87.719	<0.001
RLPLCA1	<---	RevLog	0.610	0.688	9.927	<0.001
RLOS1	<---	RevLog	0.841	0.009	90.224	<0.001
CABR1	<---	CompAdv	1.000			
CAMS1	<---	CompAdv	0.561	0.026	21.267	<0.001
CACL1	<---	CompAdv	0.501	0.027	18.259	<0.001
CARI1	<---	CompAdv	0.352	0.019	18.743	<0.001

Source: Research Data, 2020

Based on table 4.43, the critical ratios were all > 1.96 with p-values < 0.05, indicating that the factor loadings are statistically significant. This means that the latent constructs of the measured models have a statistically significant relationship. To further establish the extent to which the factors load on the components the unstandardized factor loadings were standardized. Table 4.44 below reveals the standardized factor loadings.

Table 4.44 ***Standardized Factor Loadings for the Measured Model of Reverse Logistics Interaction with Competitive Advantage***

Factor	<---	Component	Standardized Factor Loadings
RLPLCA1	<---	RevLog	0.632
RLGS1	<---	RevLog	0.997
RLCE1	<---	RevLog	0.993
RLOS1	<---	RevLog	0.998
CACL1	<---	CompAdv	0.991
CAMS1	<---	CompAdv	0.899
CABR1	<---	CompAdv	0.835
CARI1	<---	CompAdv	0.999

Source: Research Data, 2020

Based on table 4.44, the standardized factor loadings range from 0.632 to 0.999. This meant that the factors were loading very highly on the components. Finally an assessment of whether the latent variables have a statistically significant relationship was done by calculating the standard error of the estimates, the critical ration and p-values. Table 4.45 below provides a summary of results.

Table 4.45 ***Unstandardized Factor Loadings for the Structured Model of Reverse Logistics Interaction with Competitive Advantage***

			Estimate	Standard Error	Critical Ratio	p-value
RevLog	<-->	CompAdv	5.254	0.734	7.162	<0.001

Source: Research Data, 2020

Based on table 4.45, the critical value was > 1.96 and the p-values was < 0.05 indicating that the factor loadings are statistically significant. This means that the latent variables of the structured model had a statistically significant relationship. Figure 4.7 below summarizes the standardized factor loadings for the measured and structured relationships between reverse logistics and competitive advantage.

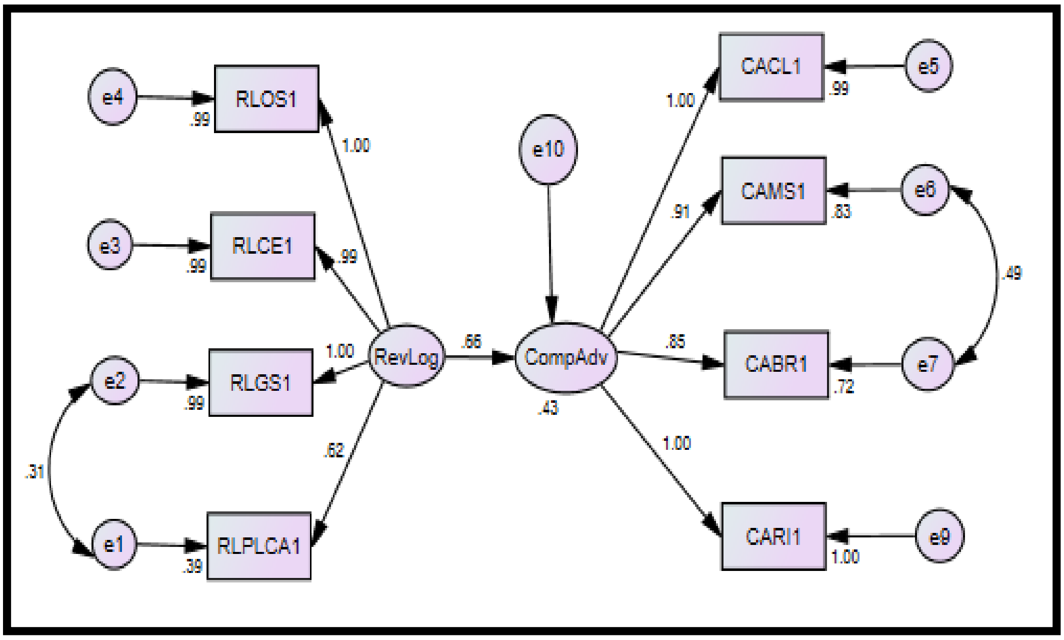


Figure 4.7. **Standardized Factor Loadings for the Measured and Structured Association linking Reverse Logistics with Competitive Advantage.**

Figure 4.7 also indicated the standardized factor loading for the latent variables reverse logistics and competitive advantage was 0.66. Since this is > 0.5 it indicated a strong association linking the latent variables

4.6.7.3 Confirmatory Factor Analysis for the Association linking Reverse Logistics, Operational Performance and Competitive Advantage

Determining the influence of operational performance on the association linking reverse logistics with competitive advantage was the second study objective. CFA was conducted using chi-square value, RMSEA, GFI, AGFI, CFI, NFI, TLI and CMIN/DF. Table 4.49 below summarizes the results of the CFA for the association linking reverse logistics, operational performance and competitive advantage.

Table 4.46 ***Overall Model Fit Results for the Association linking Reverse Logistics, Operational Performance and Competitive Advantage***

Test	Decision Criteria	Model Result
Chi-Square	Small	201.009
Degrees of Freedom		44
GFI	>0.90	0.827
CFI	>0.90	0.962
AGFI	>0.90	0.694
NFI	0.8<NFI<1.00	0.952
TLI	>0.90	0.943
RMSEA	<0.08	0.154
CMIN/DF	<5	4.568

Source: Research Data, 2020

Based on the outcome in table 4.46 the chi-square square value of 201.009, 44 degrees of freedom, RMSEA of 0.154 and a GFI of 0.827, indicated the model had good absolute fit. The AGFI, CFI, NFI and TLI had coefficients of 0.694, 0.962, 0.952 and 0.943. NFI was within the range between 0.80 and 1.00. CFI and TLI were > 0.9. AGFI was not significantly low. This model therefore exhibited a moderately good incremental fit. Parsimonious model fitness was assessed using CMIN/DF which was 4.568, suggesting a good parsimonious fit. Figure 4.8 below reveals the overall structural equation model among reverse logistics, operational performance and competitive advantage.

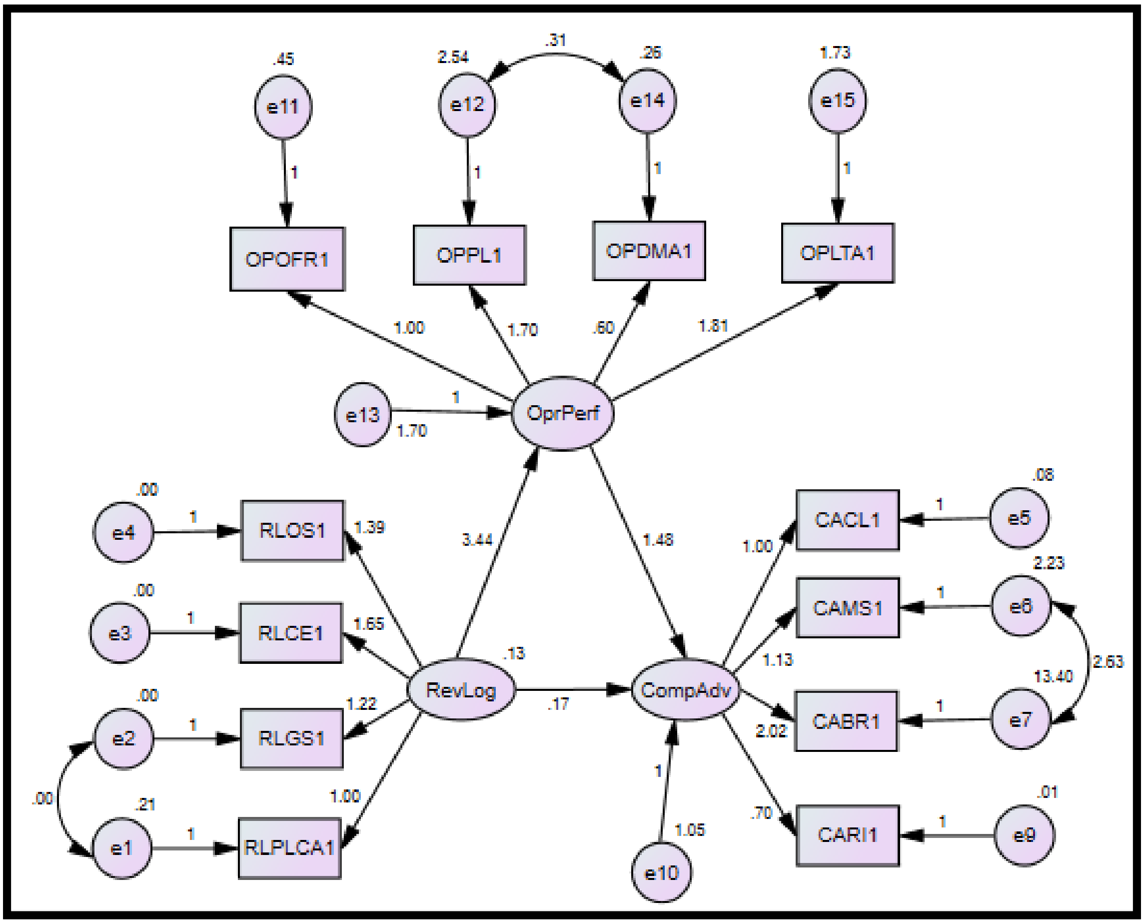


Figure 4.8. **Unstandardized Structural Equation Model for the Association linking Reverse Logistics, Operational Performance and Competitive Advantage.**

To assess the extent to which the unstandardized factor loadings are statistically significant, the standard error of the estimates, the critical ration and p-values were calculated. Table 4.47 below provides a summary of these.

Table 4.47 ***Unstandardized Factor Loadings for the Measured Model on the Association linking Reverse Logistics, Operational Performance and Competitive Advantage***

Factor	<---	Component	Estimate	Standard Error	Critical Ratio	p-value
RLCE1	<---	RevLog	1.000			
RLGS1	<---	RevLog	0.739	0.008	88.291	<0.001
RLPLCA1	<---	RevLog	0.607	0.063	9.680	<0.001
RLOS1	<---	RevLog	0.841	0.009	90.590	<0.001
OPLTA1	<---	OprPerf	1.000			
OPDMA1	<---	OprPerf	0.329	0.017	19.054	<0.001
OPPL1	<---	OprPerf	0.939	0.052	18.100	<0.001
OPOFR1	<---	OprPerf	0.552	0.026	21.646	<0.001
CABR1	<---	CompAdv	1.000			
CACL1	<---	CompAdv	0.495	0.026	19.338	<0.001
CAMS1	<---	CompAdv	0.559	0.026	21.450	<0.001
CARI1	<---	CompAdv	0.345	0.018	19.481	<0.001

Source: Research Data, 2020

Based on table 4.47 above the critical values were all > 1.96 with p-values < 0.05 suggesting that the factor loadings are statistically significant. This meant that the latent constructs of the measured models had a statistically significant relationship. The unstandardized factor loadings were standardized to determine the degree to which the factors load on the components. Table 4.48 reveals the standardized factor loadings.

Table 4.48 ***Standardized Factor Loadings for the Measured Model on the Association linking Reverse Logistics, Operational Performance and Competitive Advantage***

Factor	<---	Component	Standardized Factor Loadings
RLPLCA1	<---	RevLog	0.622
RLGS1	<---	RevLog	0.997
RLCE1	<---	RevLog	0.994
RLOS1	<---	RevLog	0.997
OPLTA1	<---	OprPerf	0.928
OPDMA1	<---	OprPerf	0.903
OPPL1	<---	OprPerf	0.888
OPOFR1	<---	OprPerf	0.938
CARI1	<---	CompAdv	0.998
CABR1	<---	CompAdv	0.848
CAMS1	<---	CompAdv	0.910
CACL1	<---	CompAdv	0.995

Source: Research Data, 2020

Based on table 4.48, the standardized factor loadings ranged between 0.622 and 0.998. This indicated a high loading of the factors on the components. This therefore meant that the factors explain the components to a large extent. Finally an analysis of whether the latent variables had a statistically significant relationship of the structured model was done by calculating the standard error of the estimates, the critical ration and p-values. Table 4.49 below reveals the results.

Table 4.49 ***Unstandardized Factor Loadings for the Structured Model on the Association linking Reverse Logistics, Operational Performance and Competitive Advantage***

Component	<-->	Component	Estimate	Standard Error	Critical Ratio	p-value
RevLog	<-->	OprPerf	3.776	0.357	10.589	<0.001
OprPerf	<-->	CompAdv	1.650	0.131	12.556	<0.001
RevLog	<-->	CompAdv	0.202	0.475	0.426	0.670

Source: Research Data, 2020

Based on table 4.49, the critical values were > 1.96 except for the structured relationship between the latent variables reverse logistics and competitive advantage. This indicates that the factor loadings for the structured relationships between reverse logistics and operational performance and between operational performance and competitive advantage were statistically significant as revealed in figure 4.9 below.

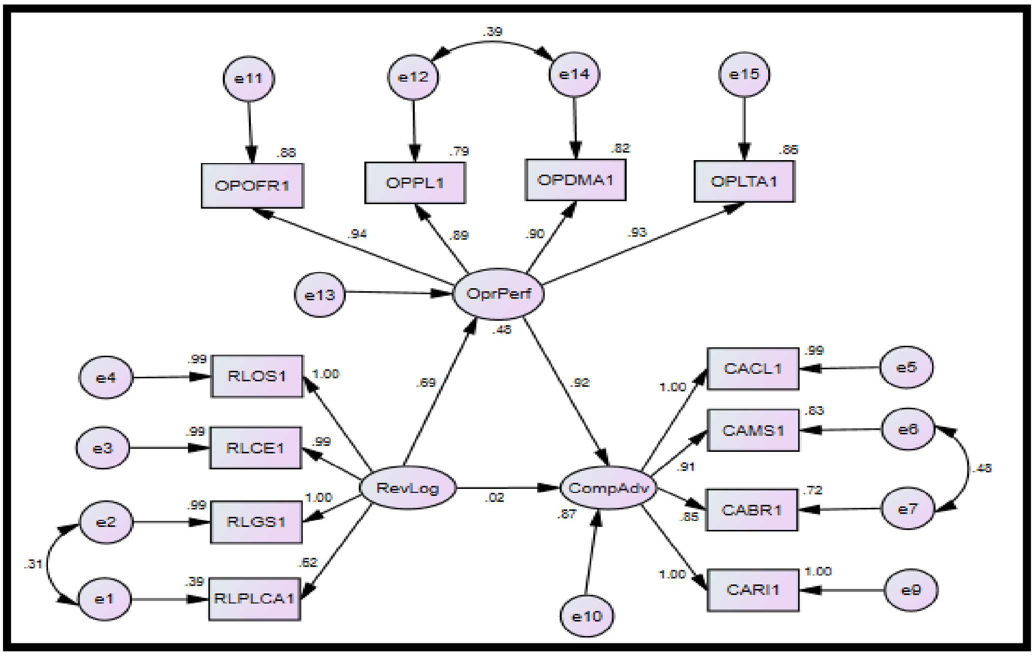


Figure 4.9. **Standardized Factor Loadings for the Measured and Structured Model Associating Reverse Logistics, Operational Performance and Competitive Advantage.**

Factor loadings for the association linking the latent constructs reverse logistics and competitive advantage was 0.02 indicating a weak association. Factor loadings for the association linking the latent construct reverse logistics and operational performance and between operational performance and competitive advantage were 0.69 and 0.92 respectively indicating relatively high association.

4.6.7.4 Confirmatory Factor Analysis for the association Linking Reverse Logistics, Process Innovation and Operational Performance

Determining the influence of process innovation on the relationship between reverse logistics and operational performance was the third study objective. CFA was assessed using chi-square value, probability level, RMSEA, GFI, AGFI, CFI, NFI, TLI and CMIN/DF. Table 4.50 below summarizes the results of the CFA.

Table 4.50 ***Overall Model Fit Results for the association linking Reverse Logistics, Process Innovation and Operational Performance***

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

Source: Research Data, 2020

Table 4.50 above, absolute fitness was assessed using chi-square, probability level, RMSEA and GFI. 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.

According to table 4.50, 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. For a good parsimonious fit the minimum discrepancy ratio is expected to be < 5. This suggests a good parsimonious fit. In conclusion the model had a fairly good overall fit. Figure 4.10 below reveals the overall structure of the CFA model.

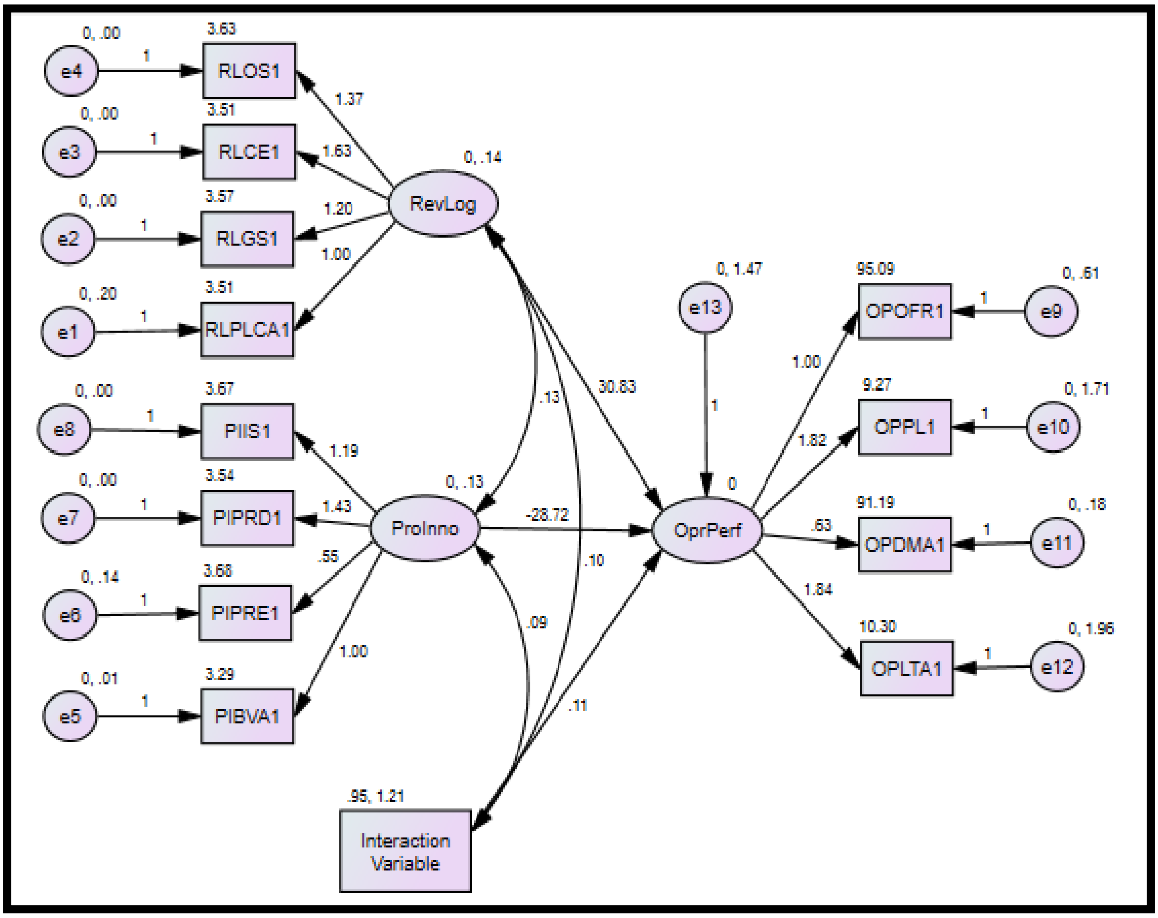


Figure 4.10. **Unstandardized Structural Equation Model for the Association linking Reverse Logistics, Process Innovation and Operational Performance.**

The standard error of the estimates of the unstandardized factor loading, the critical ration and p-values were calculated to assess whether the factor loadings are statistically significant. Table 4.51 summarizes the unstandardized factor loadings.

Table 4.51 ***Unstandardized Factor Loadings for the Measured Model on the Association linking Reverse Logistics, Process Innovation and Operational Performance***

Factor	<---	Component	Estimate	Standard Error	Critical Ratio	p-value
RLCE1	<---	RevLog	1.000			
RLGS1	<---	RevLog	0.737	0.008	95.526	<0.001
RLPLCA1	<---	RevLog	0.614	0.062	9.931	<0.001
RLOS1	<---	RevLog	0.839	0.009	92.476	<0.001
PIPRD1	<---	ProInno	1.000			
PIIS1	<---	ProInno	0.833	0.010	84.351	<0.001
PIPRE1	<---	ProInno	0.383	0.061	6.271	<0.001
PIBVA1	<---	ProInno	0.699	0.016	45.071	<0.001
OPLTA1	<---	OprPerf	1.000			
OPPL1	<---	OprPerf	0.990	0.050	19.804	<0.001
OPDMA1	<---	OprPerf	0.344	0.017	20.376	<0.001
OPOFR1	<---	OprPerf	0.544	0.029	19.073	<0.001

Source: Research Data, 2020

Based on table 4.51 the critical values are > 1.96 with p-values < 0.05 indicating statistical significance of factor loadings. In order to determine the degree to which the factors load on the components, the unstandardized factor loadings were standardized as revealed in table 4.52 below.

Table 4.52 ***Standardized Factor Loadings for the Measured Model Associating Reverse Logistics, Process Innovation and Operational Performance***

Factor	<---	Component	Estimate

RLPLCA1	<---	RevLog	0.631
RLGS1	<---	RevLog	0.997
RLCE1	<---	RevLog	0.995
RLOS1	<---	RevLog	0.996
PIBVA1	<---	ProInno	0.969
PIIS1	<---	ProInno	0.994
PIPRE1	<---	ProInno	0.657
PIPRD1	<---	ProInno	0.996
OPLTA1	<---	OprPerf	0.918
OPDMA1	<---	OprPerf	0.934
OPPL1	<---	OprPerf	0.926
OPOFR1	<---	OprPerf	0.914

Source: Research Data, 2020

Based on table 4.52 above, the least standardized factor loading was 0.631 and highest was 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, the critical ration and p-values were performed as revealed in table 4.53 below.

Table 4.53 ***Unstandardized Factor Loadings for the Structured Model Associating Reverse Logistics, Operational Performance and Competitive Advantage***

Component	<-->	Component	Estimate	Standard Error	Critical Ratio	p-value
RevLog	<-->	ProInno	0.303	0.035	8.618	<0.001
RevLog	<-->	IntVar	0.155	0.055	2.793	0.005
ProInno	<-->	IntVar	0.129	0.047	0.929	0.006

Source: Research Data, 2020

Based on table 4.53, the critical values were in the region > 1.96 with p-values < 0.05 indicating that the factor loadings were statistically significant. This meant that the latent variables of the structured equation model had statistically significant relationship. Figure

4.11 also indicates the standardized factor loading for the latent variables reverse logistics, process innovation and operational performance.

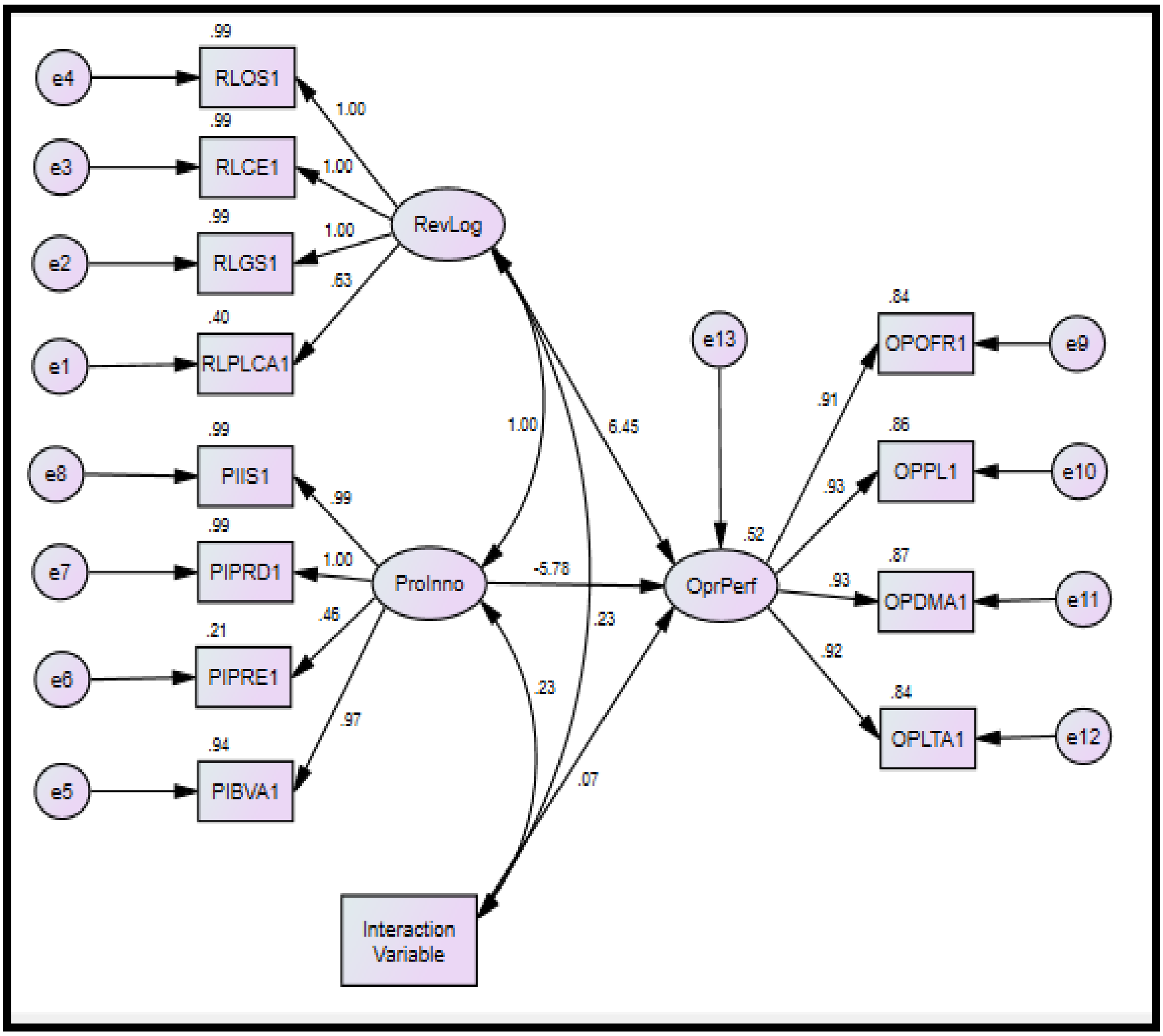


Figure 4.11. **Standardized Factor Loadings for the Measured and Structured Model Associating Reverse Logistics, Process Innovation and Operational Performance.**

Factor loadings in figure 4.11 for the association linking the latent variables reverse logistics, process innovation, the interaction variable and operational performance were 6.45, -5.78 and 0.07 respectively.

4.6.7.5 Confirmatory Factor Analysis for the Moderated – Mediation Relationship

Examining the conditional indirect effect on the association among reverse logistics, process innovation and operational performance on a firm's competitive advantage was the fourth study objective. CFA was performed using chi-square value, RMSEA, GFI, AGFI, CFI, NFI, TLI and CMIN/DF. Table 4.54 below summarizes the results thereof.

Table 4.54 ***Overall Model Fit Results for the Moderated – Mediation Relationship***

Test	Decision Criteria	Model Result
Chi-Square	Small	665.019
Degrees of Freedom		106
GFI	>0.90	0.743
CFI	>0.90	0.907
AGFI	>0.90	0.629
NFI	0.8<NFI<1.00	0.892
TLI	>0.90	0.881
RMSEA	<0.08	0.188
CMIN/DF	<5	6.274

Source: Research Data, 2020

Table 4.54 above reveals a chi-square value of 665.019 which is considered to be fairly small because the number of degrees of freedom is 106. RMSEA was 0.188 which is > 0.08 and GFI was 0.743. This reveals a fairly good absolute fit. Based on the table 4.54, AGFI, CFI, NFI and TLI had coefficients of 0.629, 0.907, 0.892 and 0.881. NFI was within the range between 0.80 and 1.00. CFI was > 0.9 and TLI was approaching the threshold of 0.9. Despite having a low AGFI of 0.629 the model exhibited a fairly good incremental fit. Parsimonious model fitness was assessed using CMIN/DF which was 6.274. A good parsimonious fit requires the minimum discrepancy ratio to be < 5. This suggests a fairly good parsimonious fit. In general the model had a fairly good overall fit. Figure 4.12 below reveals the structured model showing the moderated- mediation relationship among reverse logistics, process innovation, operational performance and competitive advantage. The figure reveals the covariance between the exogenous variables and the unstandardized factor loadings.

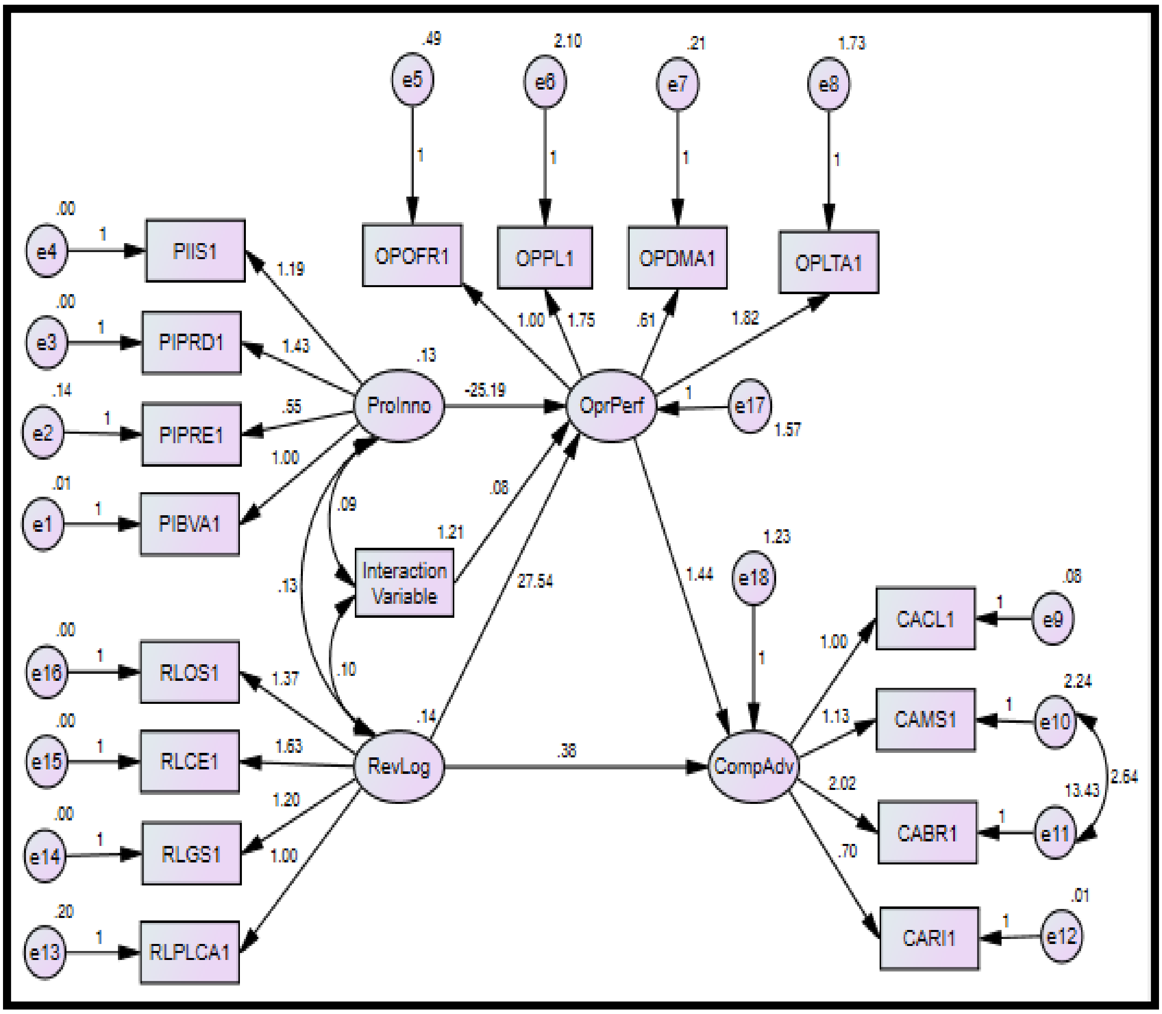


Figure 4.12. **Confirmatory Factor Analysis Model for the Moderated-Mediation Relationship**

The standard error of the estimates of the unstandardized factor loading, the critical ration and p-values were calculated to assess the statistical significance of the factor loadings as revealed in table 4.55 below.

Table 4.55 ***Unstandardized Factor Loadings for the Measured Model on the Moderated - Mediation Relationship***

Factor	<---	Component	Estimate	Standard Error	Critical Ratio	p-value
RLCE1	<---	RevLog	1.000			
RLGS1	<---	RevLog	0.737	0.008	95.553	<0.001
RLPLCA1	<---	RevLog	0.614	0.062	9.930	<0.001
RLOS1	<---	RevLog	0.839	0.009	92.578	<0.001
PIPRD1	<---	ProInno	1.000			
PIPRE1	<---	ProInno	0.383	0.061	6.280	<0.001
PIBVA1	<---	ProInno	0.699	0.016	45.081	<0.001
PIIS1	<---	ProInno	0.833	0.010	84.307	<0.001
OPLTA1	<---	OprPerf	1.000			
OPDMA1	<---	OprPerf	0.336	0.016	20.481	<0.001
OPPL1	<---	OprPerf	0.960	0.049	19.479	<0.001
OPOFR1	<---	OprPerf	0.548	0.026	21.187	<0.001
CABR1	<---	CompAdv	1.000			
CAMS1	<---	CompAdv	0.559	0.026	21.443	<0.001
CACL1	<---	CompAdv	0.495	0.026	19.300	<0.001
CARI1	<---	CompAdv	0.345	0.018	19.461	<0.001

Source: Research Data, 2020

Based on table 4.55 the critical values were > 1.96 with p-values < 0.05 indicating the factor loadings are statistically significant. To determine the degree to which the factors load on the components, the unstandardized factor loadings were standardized as revealed in table 4.56 below.

Table 4.56 ***Standardized Factor Loadings for the Measured Model on the Moderated – Mediation Model***

Factor	<---	Component	Standardized Factor Loadings
RLPLCA1	<---	RevLog	0.631
RLGS1	<---	RevLog	0.997
RLCE1	<---	RevLog	0.995
RLOS1	<---	RevLog	0.996
PIBVA1	<---	ProInno	0.969
PIPRE1	<---	ProInno	0.657
PIPRD1	<---	ProInno	0.996
PIIS1	<---	ProInno	0.994
OPLTA1	<---	OprPerf	0.928
OPDMA1	<---	OprPerf	0.922
OPPL1	<---	OprPerf	0.908
OPOFR1	<---	OprPerf	0.931
CARI1	<---	CompAdv	0.999
CABR1	<---	CompAdv	0.848
CAMS1	<---	CompAdv	0.909
CACL1	<---	CompAdv	0.995

Source: Research Data, 2020

Based on table 4.56, the least standardized factor loading was 0.631 and the highest as 0.999. This therefore meant that the factors explain the components to a large extent. To check the statistical significance among the latent variables of the structured model, calculations of the standard error of the estimates, the critical ration and p-values were performed as revealed in table 4.57 below.

Table 4.57 ***Unstandardized Factor Loadings for the Structured Model on the Moderated – Mediation Model***

Component	<-->	Component	Estimate	Standard Error	Critical Ratio	p-value
RevLog	<-->	ProInno	0.303	0.035	8.618	<0.001
RevLog	<-->	IntVar	0.129	0.047	2.757	0.006
ProInno	<-->	IntVar	0.155	0.055	2.793	0.005
RevLog	<-->	CompAdv	0.469	0.485	0.966	0.334
RevLog	<-->	OprPerf	-32.137	39.830	-0.807	0.420
OprPerf	<-->	CompAdv	1.595	0.131	12.214	<0.001

Source: Research Data, 2020

Based on table 4.57, the critical ratio for the covariance relationships between reverse logistics, process innovation and the interaction variable were > 1.96 with p-values < 0.05 showing that moderation was statistically significant. The critical ratio between the latent variable reverse logistics and competitive advantage and between reverse logistics and operational performance were < 1.96 with p-values > 0.05 however the critical ratio between operational performance and competitive advantage was > 1.96 with a p-value < 0.05 showing a statistically significant mediation relationship. Therefore the moderated-mediation relationship was statistically significant.

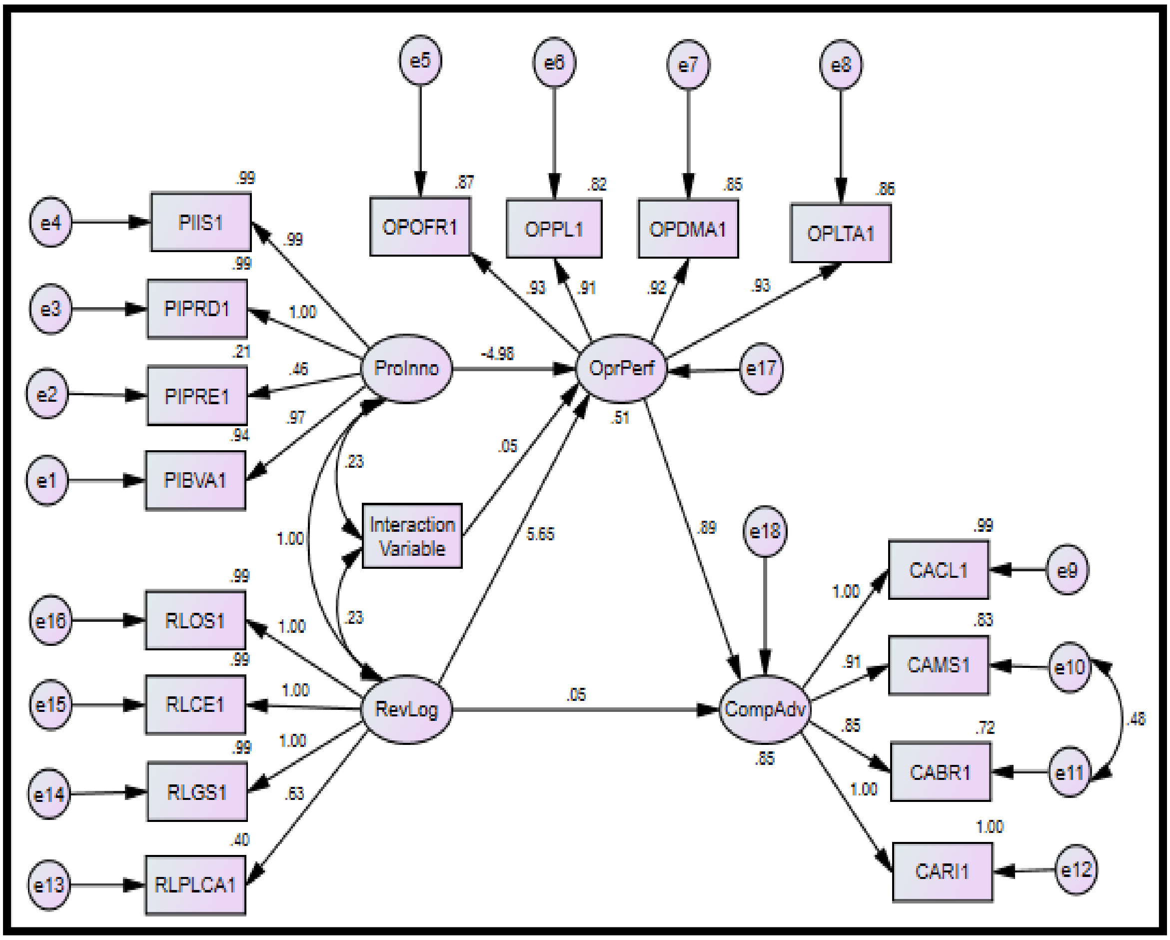


Figure 4.13. **Standardized Factor Loadings for the Measured and Structured relationships for the Moderated – Mediation Model**

Figure 4.13 indicates standardized factor loadings for the relationship between the latent constructs reverse logistics and competitive advantage was 0.05 indicating a weak association. Factor loadings for the association linking the interaction variable and operational performance was 0.05 indicating a weak moderation effect in the moderated – mediation relationship. Factor loadings for the association linking the latent construct operational performance and competitive advantage was 0.89 indicating strong mediation effect when considering the moderated – mediation relationship.

4.6.7.6 Confirmatory Factor Analysis for the Joint association linking Reverse Logistics, Process Innovation, Operational Performance and Competitive Advantage

Examining the joint effect of reverse logistics, process innovation and operational performance on a firm's competitive advantage was the last study objective. Table 4.58 below summarizes the results of the CFA for the relationship among the latent variables.

Table 4.58 ***Overall Model Fit Results for the Joint Relationship between Reverse Logistics, Process Innovation, Operational Performance and Competitive Advantage***

Test	Decision Criteria	Model Result
Chi-Square	Small	547.531
Degrees of Freedom		94
GFI	>0.90	0.747
CFI	>0.90	0.904
AGFI	>0.90	0.583
NFI	0.8<NFI<1.00	0.890
TLI	>0.90	0.877
RMSEA	<0.08	0.202
CMIN/DF	<5	5.824

Source: Research Data, 2020

Table 4.58 above reveals chi-square value of 547.531, RMSEA of 0.202 which is > 0.08 and the GFI of 0.747 indicating fairly good absolute fit. Based on table 4.58, AGFI, CFI, NFI and TLI had coefficients of 0.583, 0.904, 0.890 and 0.877. NFI was within the range between 0.80 and 1.00. CFI was > 0.90 and TLI was approaching the threshold of 0.9. Despite having a low AGFI of 0.583 the model exhibited a fairly good incremental fit. Parsimonious model fitness was assessed using CMIN/DF which was 5.824. A good parsimonious fit requires the minimum discrepancy ratio to be < 5. However 5.824 was approaching the threshold. This suggests a fairly good parsimonious fit. In general the model had a fairly good overall fit. Figure 4.14 below reveals the overall structure of the structural model for the joint effect among the latent variables.

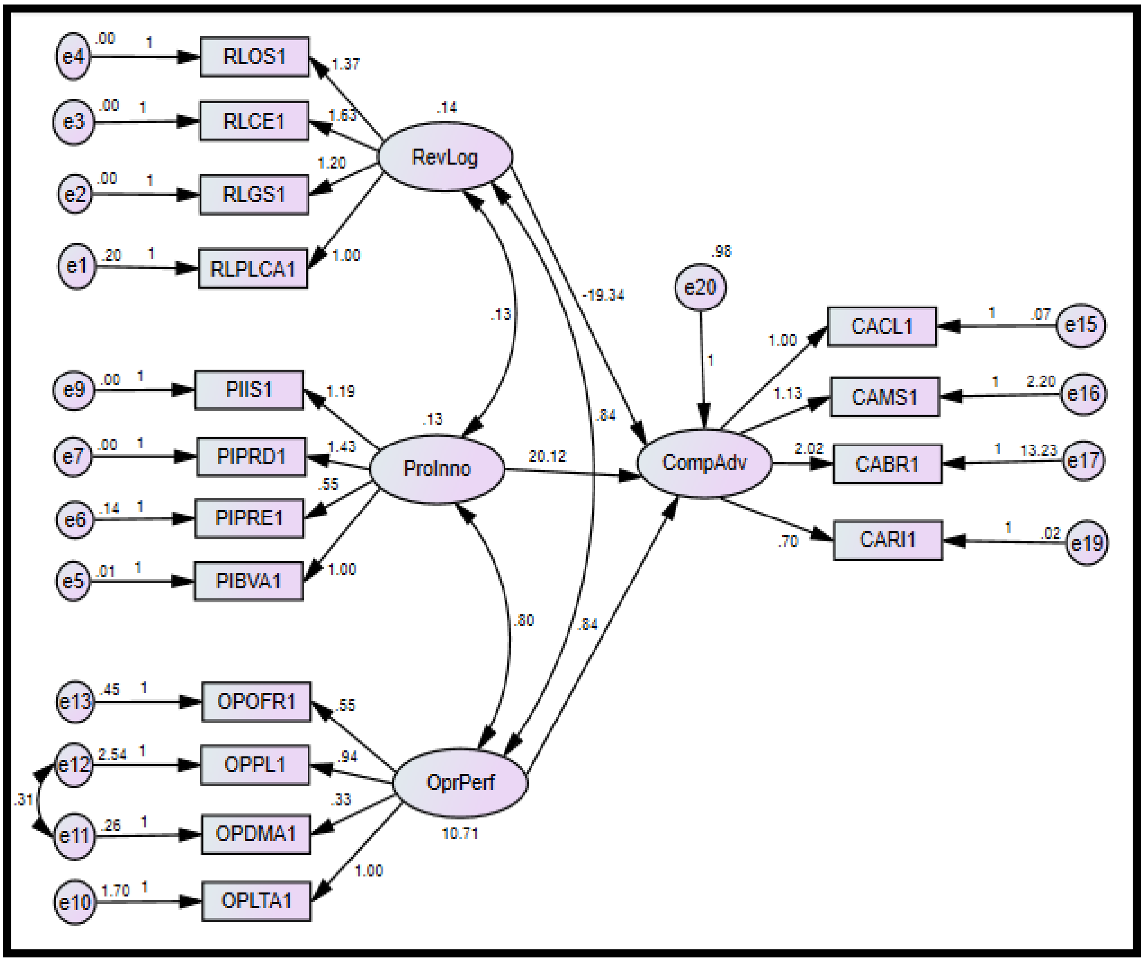


Figure 4.14. **Structural Model for the Joint Relationship among Reverse Logistics, Process Innovation, Operational Performance and Competitive Advantage**

The standard error of the estimates of the unstandardized factor loading, the critical ration and p-values were calculated to assess whether the factor loadings are statistically significant. Table 4.59 below provides a summary of results for the unstandardized factor loadings.

Table 4.59 ***Unstandardized Factor Loadings for the Measured Model of the Joint Relationship***

Factor	<---	Component	Estimate	Standard Error	Critical Ratio	p-value
RLCE1	<---	RevLog	1.000			
RLGS1	<---	RevLog	0.737	0.008	95.607	<0.001
RLPLCA1	<---	RevLog	0.614	0.062	9.914	<0.001
RLOS1	<---	RevLog	0.839	0.009	92.467	<0.001
PIPRD1	<---	ProInno	1.000			
PIPRE1	<---	ProInno	0.383	0.061	6.286	<0.001
PIBVA1	<---	ProInno	0.699	0.016	45.071	<0.001
PIIS1	<---	ProInno	0.833	0.010	84.313	<0.001
OPLTA1	<---	OprPerf	1.000			
OPDMA1	<---	OprPerf	0.329	0.017	19.174	<0.001
OPPL1	<---	OprPerf	0.938	0.052	18.165	<0.001
OPOFR1	<---	OprPerf	0.551	0.025	21.645	<0.001
CABR1	<---	CompAdv	1.000			
CACL1	<---	CompAdv	0.494	0.025	19.521	<0.001
CAMS1	<---	CompAdv	0.558	0.035	15.937	<0.001
CARI1	<---	CompAdv	0.344	0.018	19.632	<0.001

Source: Research Data, 2020

Based on table 4.59, the critical values were >1.96 with p-values < 0.05 indicating that the factor loadings are statistically significant. To determine the degree to which the factors load on the components, the unstandardized factor loadings were standardized as revealed in table 4.60 below.

Table 4.60 ***Standardized Factor Loadings for the Measured Model for the Joint Relationship***

Factor	<---	Component	Standardized Factor Loadings
RLPLCA1	<---	RevLog	0.631
RLGS1	<---	RevLog	0.997
RLCE1	<---	RevLog	0.995
RLOS1	<---	RevLog	0.996
PIBVA1	<---	ProInno	0.969
PIPRE1	<---	ProInno	0.657
PIPRD1	<---	ProInno	0.996
PIIS1	<---	ProInno	0.994
OPLTA1	<---	OprPerf	0.929
OPDMA1	<---	OprPerf	0.904
OPPL1	<---	OprPerf	0.888
OPOFR1	<---	OprPerf	0.937
CARI1	<---	CompAdv	0.998
CABR1	<---	CompAdv	0.850
CAMS1	<---	CompAdv	0.911
CACL1	<---	CompAdv	0.996

Source: Research Data, 2020

Based on table 4.60, the least standardized factor loading was 0.631 and highest 0.998. This therefore meant that the factors explain the components to a large extent. To check if a statistically significant association among the latent variables of the structured model was present, calculations of the standard error of the estimates, the critical ration and p-values were performed as revealed in table 4.61 below.

Table 4.61 ***Unstandardized Factor Loadings for the Structured Model for the Joint Relationship***

Component	<-->	Component	Estimate	Standard Error	Critical Ratio	p-value
RevLog	<-->	ProInno	0.303	0.035	8.618	<0.001
RevLog	<-->	OprPerf	1.362	0.202	6.738	<0.001
ProInno	<-->	OprPerf	1.140	0.170	6.692	<0.001
CompAdv	<-->	RevLog	-24.023	33.072	-0.726	0.468
CompAdv	<-->	ProInno	28.478	38.749	0.735	0.462
CompAdv	<-->	OprPerf	1.704	0.163	10.453	< 0.001

Source: Research Data, 2020

Based on table 4.61, the covariance relationship among reverse logistics, process innovation and operational performance had critical values >1.96 with a p-value < 0.05 pointing out that the factor loadings were statistically significant. The relationship between the latent variables operational performance and competitive advantage was also >1.96 with a p-value < 0.05. Figure 4.15 below, indicates the standardized factor loading for the latent variables. Factor loadings for the relationship between the latent variables reverse logistics, process innovation and operational performance on competitive advantage were -2.45, 2.46 and 0.95 respectively.

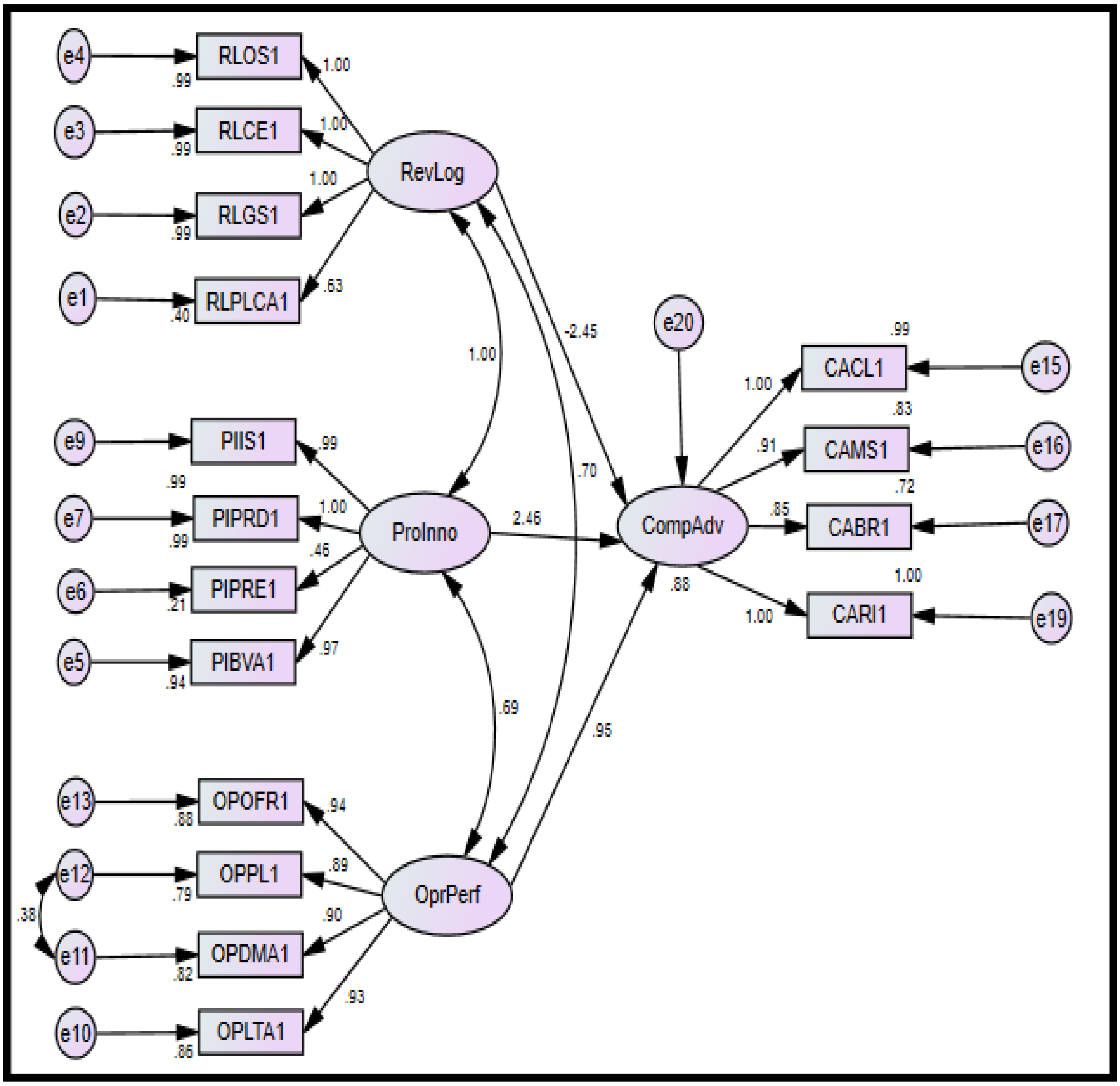


Figure 4.15. **Standardized Factor Loadings for the Measured and Structured relationships for the Joint Model**

4.7 Common Method Variance

In the CLF method for each latent variable, the CMV is the square of the common factor of each path before standardization. It can also be obtained by getting the difference between the standardized regression weights with CLF and without the CLF. The difference between the two weights should be < 0.20. The ensuing sub-sections discuss the CMV tests performed for each of the five objectives of the study.

4.7.1 Common Method Variance Test on the Reverse Logistics link with Competitive Advantage.

Establishing the influence of reverse logistics on competitive advantage was the first study objective. CMV was assessed to determine whether it was necessary to include the common method latent variable while performing hypothesis test. Figure 4.16 reveals the results of the CLF method performed on the association linking reverse logistics with competitive advantage.

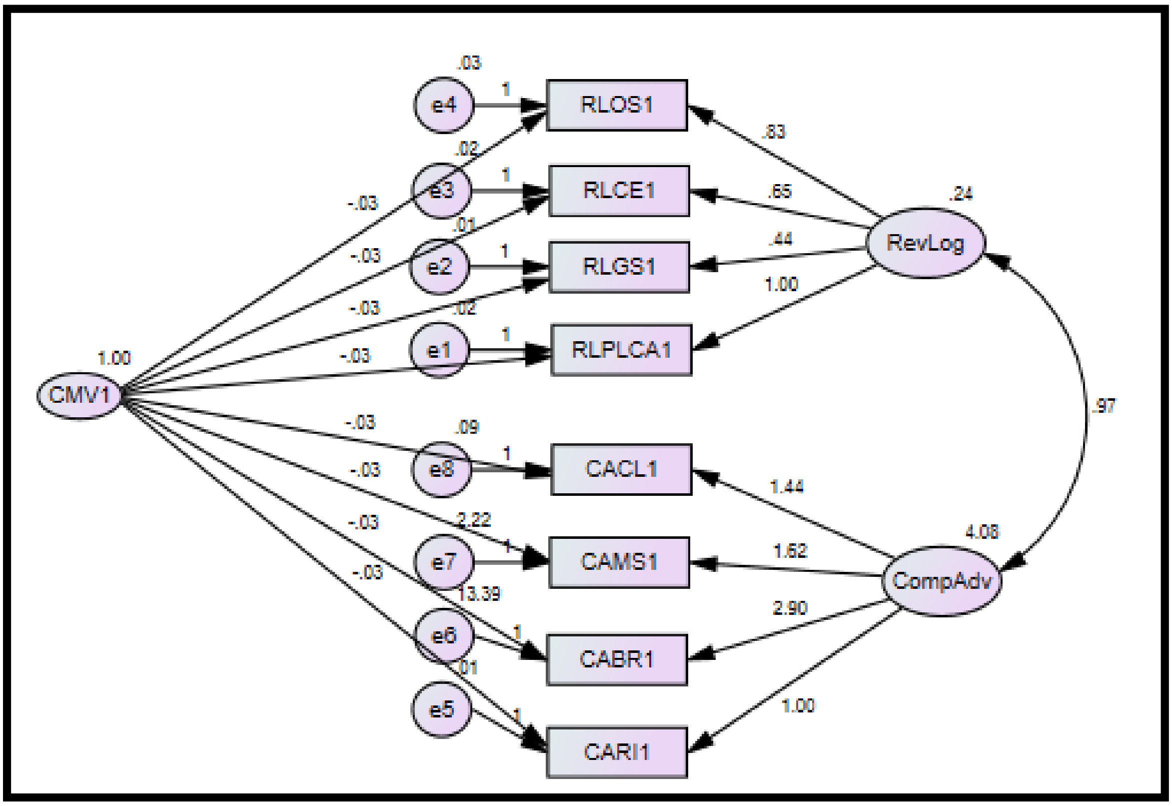


Figure 4.16. **Common Latent Factor Analysis Model for Reverse Logistics interaction with Competitive Advantage.**

Based on figure 4.16 above, the CLF for each of the variables was - 0.03. This therefore gives a common method variance of 0.0009 which is < 0.5 for each of the variables. This means that the model is not affected by spurious correlation between variables. Table 4.62 below reveals the results of the CLF method obtained by getting the difference between the standardized regression weights with the CLF and without the CLF.

Table 4.62 ***Common Latent Factor Difference Analysis Model for Reverse Logistics interaction with Competitive Advantage***

Factor	<---	Component	Standardized Regression Weights with CLF	Standardized Regression Weights with no CLF	Difference
RLPLCA1	<---	RevLog	0.964	0.964	0.000
RLGS1	<---	RevLog	0.771	0.934	0.163
RLCE1	<---	RevLog	0.728	0.905	0.177
RLOS1	<---	RevLog	0.747	0.921	0.174
CARI1	<---	CompAdv	1.001	0.999	-0.002
CABR1	<---	CompAdv	0.842	0.848	0.006
CAMS1	<---	CompAdv	0.905	0.910	0.005
CACL1	<---	CompAdv	0.993	0.995	0.002

Source: Research Data, 2020

Based on table 4.62 the difference between the standardized regression weights without the CLF and with CLF were < 0.20 again indicating the model is not affected by spurious correlations. Therefore it will not be necessary to include the common method latent variable while performing the hypothesis test.

4.7.2 Common Method Variance Test on the Association linking Reverse Logistics, Operational Performance and Competitive Advantage

Determining the influence of operational performance on the interaction linking reverse logistics with competitive advantage was the second objective. CMV was assessed to determine whether it was necessary to include the common method latent variable while performing hypothesis test as revealed in figure 4.17 below.

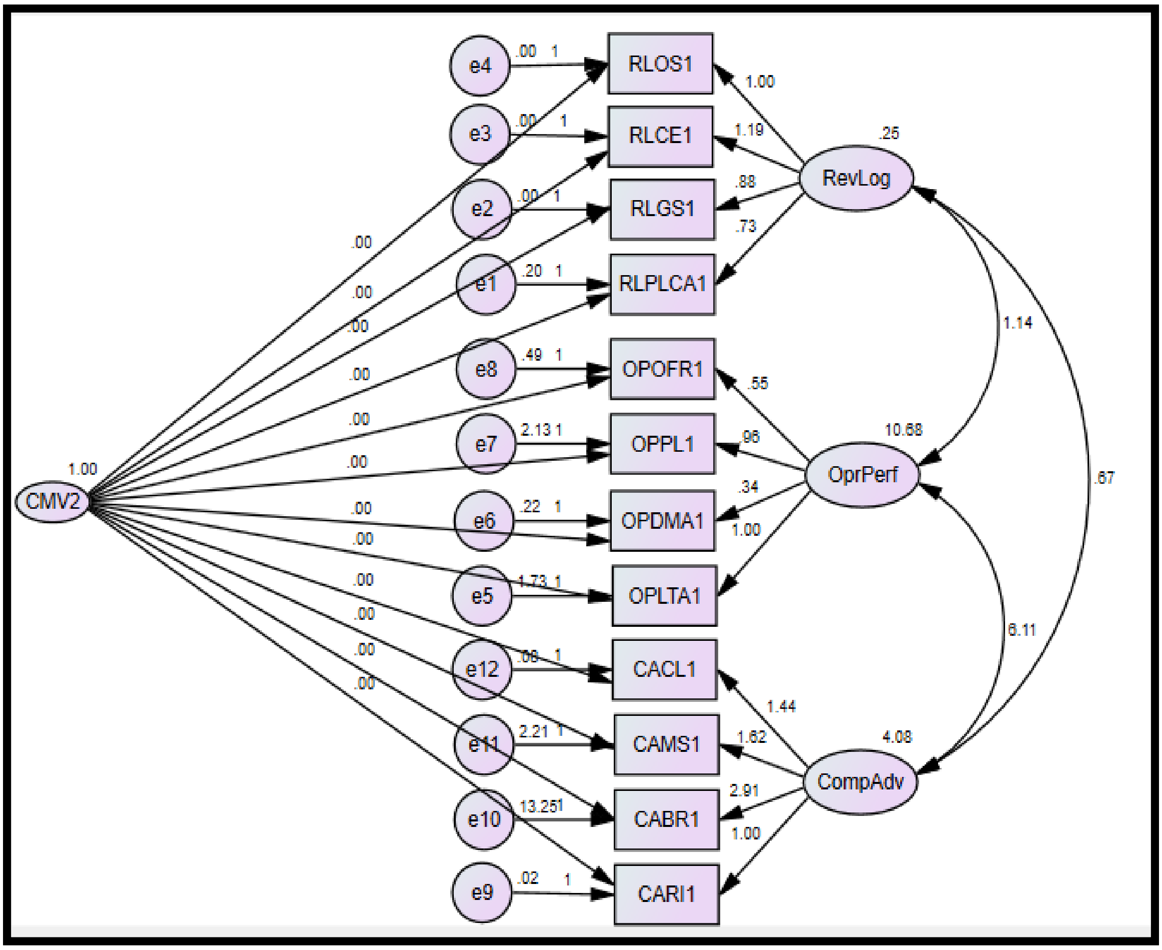


Figure 4.*17*. Common Latent Factor Analysis Model for the Association linking Reverse Logistics, Operational Performance and Competitive Advantage.

Based on figure 4.17 above the common latent factor for each of the variables was 0.00. This therefore gives a common method variance of 0.0000 which is < 0.5 for each of the variables. This means that the model is not affected by spurious correlations. Table 4.63 below reveals the results of the common latent factor method.

Table 4.63 ***Common Latent Factor Difference Analysis Model for the Association linking Reverse Logistics, Operational Performance and Competitive Advantage***

Factor	<---	Component	Standardized Regression Weights with CLF	Standardized Regression Weights with no CLF	Difference
RLPLCA1	<---	F1	0.630	0.630	0.000
RLGS1	<---	F1	0.997	0.997	0.000
RLCE1	<---	F1	0.993	0.993	0.000
RLOS1	<---	F1	0.997	0.997	0.000
OPLTA1	<---	F3	0.928	0.928	0.000
OPDMA1	<---	F3	0.920	0.920	0.000
OPPL1	<---	F3	0.907	0.907	0.000
OPOFR1	<---	F3	0.932	0.932	0.000
CARI1	<---	F4	0.998	0.998	0.000
CABR1	<---	F4	0.850	0.850	0.000
CAMS1	<---	F4	0.911	0.911	0.000
CACL1	<---	F4	0.996	0.996	0.000

Source: Research Data, 2020

Based on table 4.63 the difference between the standardized regression weights without the CLF and with CLF < 0.20 therefore it confirmed that it will not be necessary to include the common method latent variable while performing the hypothesis test.

4.7.3 Common Method Variance Test on the Association linking Reverse Logistics, Process Innovation and Operational Performance

Determining the influence of process innovation on the association linking reverse logistics and operational performance was the third objective of the study. Figure 4.18 reveals the results of the common latent factor method performed on the relationship among the latent variables.

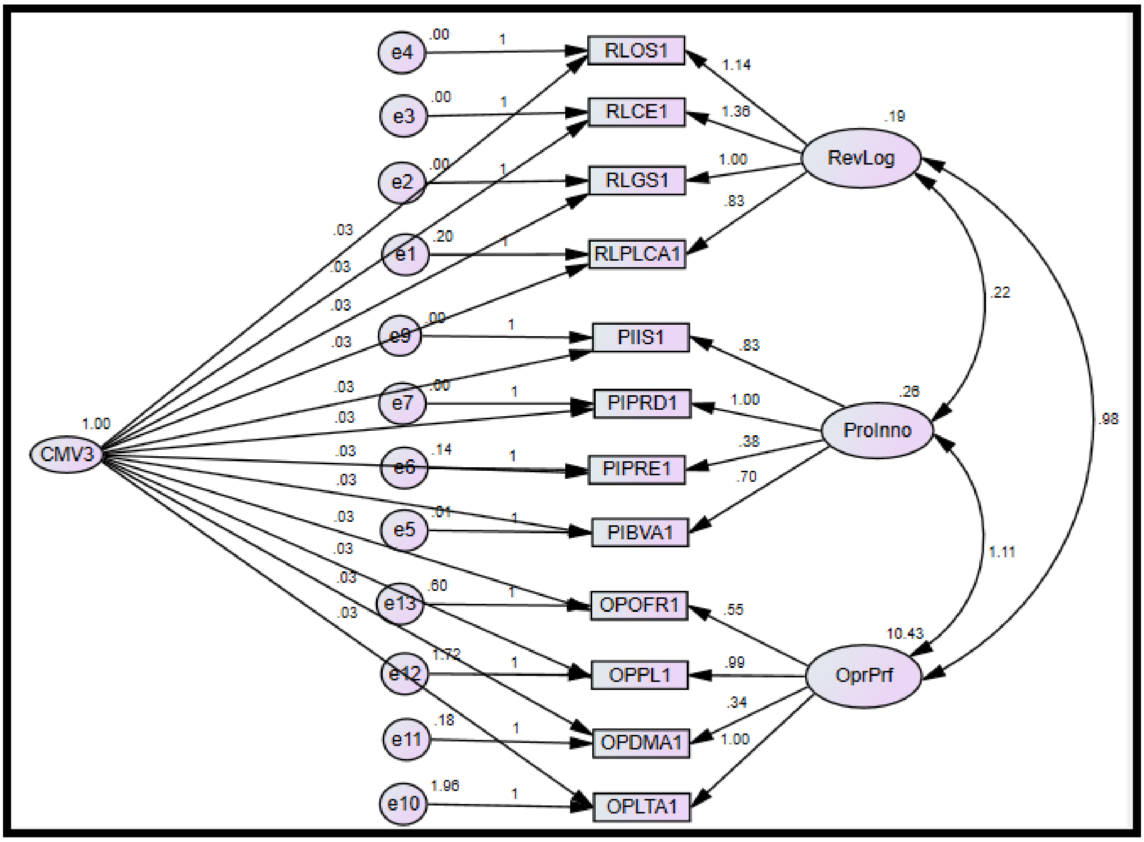


Figure 4.18. **Common Latent Factor Analysis Model for the Association linking Reverse Logistics Process Innovation and Operational Performance.**

Based on figure 4.18, the common latent factor was each of the variables was 0.03. This therefore gives a common method variance of 0.0009 which is < 0.5 for each of the variables. This means that the model is not affected by spurious correlations. Table 4.64 below reveals the results of the common latent factor method.

Table 4.64 ***Common Latent Factor Difference Analysis Model for the Association linking Reverse Logistics, Process Innovation and Operational Performance***

Factor	<---	Component	Standardized Regression Weights with CLF	Standardized Regression Weights with no CLF	Difference
RLPLCA1	<---	F1	0.629	0.631	-0.002
RLGS1	<---	F1	0.995	0.997	-0.002
RLCE1	<---	F1	0.994	0.995	-0.001
RLOS1	<---	F1	0.995	0.996	-0.001
PIBVA1	<---	F2	0.967	0.969	-0.002
PIPRE1	<---	F2	0.454	0.457	-0.003
PIPRD1	<---	F2	0.995	0.996	-0.001
PIIS1	<---	F2	0.992	0.994	-0.002
OPLTA1	<---	F3	0.917	0.918	-0.001
OPDMA1	<---	F3	0.933	0.933	0.000
OPPL1	<---	F3	0.925	0.925	0.000
OPOFR1	<---	F3	0.915	0.916	-0.001
OPUVC1	<---	F3	0.629	0.631	-0.002

Source: Research Data, 2020

Based on table 4.64 the difference between the standardized regression weights without the CLF and with CLF < 0.20 therefore it confirmed that it will not be necessary to include the common method latent variable while performing the hypothesis test.

4.7.4 Common Method Variance Test on the Association linking Reverse Logistics, Process Innovation, Operational Performance and Competitive Advantage

Examining the conditional indirect effect on the relationship among reverse logistics, process innovation and operational performance on a firm's competitive advantage was the fourth study objective. Further examining the joint effect of the latent variables was the last study objective. For both of these objectives common method variance was assessed to determine whether it was necessary to include the common method latent variable while performing hypotheses tests as revealed in figure 4.19 below.

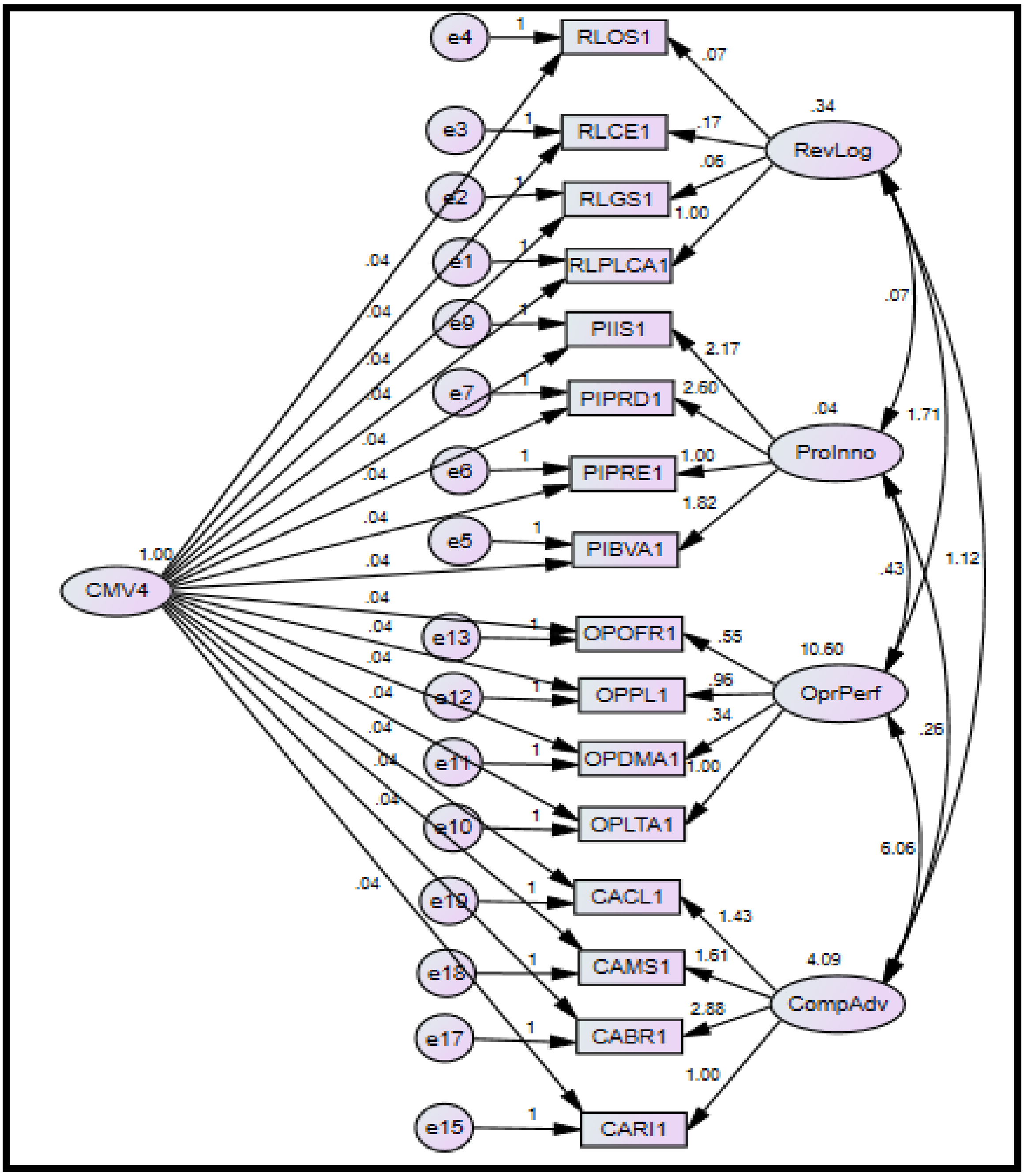


Figure 4.19. **Common Latent Factor Analysis Model for the Association linking Reverse Logistics, Process Innovation, Operational Performance and Competitive Advantage**

Based on figure 4.19 below, the common latent factor for each of the variables was 0.04. This therefore gives a common method variance of 0.0016 which is < 0.5 for each of the variables. This meant that the models were not affected by spurious correlations. Table 4.65 reveals the results of the common latent factor method.

Table 4.65 ***Common Latent Factor Difference Analysis Model for the Association linking Reverse Logistics, Process Innovation, Operational Performance and Competitive Advantage***

Factor	<---	Component	Standardized Regression Weights with CLF	Standardized Regression Weights with no CLF	Difference
RLPLCA1	<---	F1	0.628	0.631	-0.003
RLGS1	<---	F1	0.995	0.997	-0.002
RLCE1	<---	F1	0.994	0.995	-0.001
RLOS1	<---	F1	0.995	0.996	-0.001
PIBVA1	<---	F2	0.965	0.982	-0.017
PIPRE1	<---	F2	0.455	0.457	-0.002
PIPRD1	<---	F2	0.990	0.944	0.046
PIIS1	<---	F2	0.992	0.982	0.010
OPLTA1	<---	F3	0.924	0.942	-0.018
OPDMA1	<---	F3	0.923	0.941	-0.018
OPPL1	<---	F3	0.909	0.902	0.007
OPOFR1	<---	F3	0.932	0.913	0.019
CARI1	<---	F4	0.999	0.996	0.003
CABR1	<---	F4	0.842	0.854	-0.012
CAMS1	<---	F4	0.906	0.910	-0.004
CACL1	<---	F4	0.993	0.997	-0.004

Source: Research Data, 2020

Based on table 4.65 the difference between the standardized regression weights without the CLF and with CLF < 0.20 therefore it confirmed that it will not be necessary to include the common method latent variable while performing the hypotheses tests.

4.8 Summary of Chapter Results

The main objective of this study was to examine the relationships among reverse logistics, process innovation, operational performance and competitive advantage of manufacturing firms in Kenya.

Prior to hypotheses testing, it was important to check whether patterns of correlations are relatively compact and whether there is a possibility of dimension reduction. KMO tests yielded values of 0.872, 0.919, 0.950 and 0.942 (Table 4.5, 4.6, 4.7 and 4.8) which were > 0.7. Sphericity tests produced p-values < 0.05. This meant that conducting CFA will produce statistically reliable factors and results. Component matrix values were > 0.5 except for the latent constructs, OPUVC1 and PIRD1. These two latent constructs were considered as potential for deletion in the models prior to hypotheses tests.

Cronbach's alpha coefficient measuring how well the questionnaire items for reverse logistics and process innovation were actually measuring the latent constructs yielded co-efficient values ranging between 0.704 and 0.744 (Table 4.9). Since they were > 0.7, these indicated sufficient internal consistency between the questionnaire items and the latent constructs. To further assess whether the questionnaire items had sufficient explanatory power on the latent constructs for reverse logistics and process innovation communality co-efficients were calculated and they were all > 0.3. In order to determine how well the latent constructs were actually measuring the latent variable cronbach's alpha yielded co-efficient values ranging between 0.897 and 0.972 (Table 4.12). These were > 0.7 showing sufficient internal consistency between the constructs and variables. Communality co-efficients ranged between 0.810 and 0.968.

Content, convergent and discriminant validity tests were performed to check for construct validity. A team of resource persons from the field of reverse logistics was used to ascertain content validity. Convergent validity was tested using SFL and AVE. SFL for the latent constructs are as shown in figure 4.2, 4.3, 4.4 and 4.5. From the figures the latent constructs CAWR1, OPUVC1 and PIRD1 had factor loadings < 0.5 for which they were deleted from the model. From table 4.14, 4.16, 4.18 and 4.20, the AVE values were > 0.5 showing good convergent validity among the constructs.

To check for discriminant validity, AVEs were compared to MSVs. The AVEs (Table 4.16) were 0.841 and 0.836 showing they were > MSV at 0.479 (Table 4.21) for reverse logistics and operational performance showing good discriminant validity among the variables. Similarly, the AVEs (Table 4.14) were 0.569 and 0.875 which shows they were > MSV at 0.440 (Table 4.21) for reverse logistics and competitive advantage. The AVEs (Table 4.18) were 0.782 and 0.852 showing they were > MSV at 0.468 (Table 4.21) for process innovation and operational performance showing good discriminant validity among the variables. Similarly, the AVEs (Table 4.20) were 0.782 and 0.883 which shows they were > MSV at 0.443 (Table 4.21) for process innovation and competitive advantage. The AVEs (Table 4.20) were 0.850 and 0.883 which shows they were almost equal to the MSV at 0.854 (Table 4.21) for operational performance and competitive advantage. All these suggested good discriminant validity among the variables.

Summary descriptive statistics for the latent variable reverse logistics, process innovation, operational performance and competitive advantage generally showed the distributions formed from the data were normally distributed. Z-skewness and z-kurtosis scores ranging between ± 1.96 (Table 4.26, 4.32, 4.34 and 4.35). Outlier test results for reverse logistics, process innovation, operational performance and competitive advantage latent constructs forming the respective latent variables ranged between -2.421 and 2.301 (Table 4.36). These were within ± 2.5 range meaning that there were no outliers.

Kolmogorov-Smirnov tests for the latent constructs indicated significance levels with the lowest at 0.058 and the highest > 0.200 (Table 4.37). From the same table, the Shapiro-Wilk test results for the latent constructs indicated significance levels ranging from 0.052 to 0.48. Since the p-values were > 0.05 we presumed that the distributions generated by the observations for each latent construct had a normal distribution.

Durbin-Watson statistic were use to test for autocorrelation. From table 4.38 the Durbin-Watson statistics ranged from 1.808 and 2.148. These were all within the acceptable region (1.788 – 2.212) meaning serial autocorrelation did not exist. Linearity tests from appendices 5, 6, 7, 8, 9 and 10 showed the p-values were significant at ά = 0.01. Correlation co-efficients ranged between 0.448 and 0.994 showing there was sufficient evidence to support linearity. Multicollinearity tests (table 4.39) revealed that the latent constructs are not significantly affected by multicollinearity. To test for heteroscedasticity, Koenker test was used with calculated statisitics values ranging from 0.055 to 0.867. Because these p-values were > 0.05, homoscedasticity was assumed.

The RMSEA for the measured model ranged between 0.000 and 0.101, while the GFI values were between 0.983 and 1.000 suggesting good absolute fit. AGFI, CFI, NFI and TLI had coefficients ranging between 0.916 and 0.996; 0.995 and 1.000; 0.993 and 1.000;

and 0.986 and 1.005 respectively suggesting good incremental fit in the models. CMIN/DF ranged between 0.122 and 2.525 suggesting good parsimonious fit (Table 4.41). In general the measured models had good overall fit.

For the structured models, the RMSEA ranged between 0.117 and 0.202, while the GFI values were between 0.743 and 0.929 suggesting fairly good absolute fit. AGFI, CFI, NFI and TLI had coefficients ranging between 0.583 and 0.841; 0.904 and 0.989; 0.890 and 0.983; and 0.877 and 0.980 respectively suggesting a fairly good incremental fit in the models. CMIN/DF ranged between 3.069 and 6.274 suggesting fairly good parsimonious fit. In general the all the models had a fairly good overall fit (Table 4.42, 4.46, 4.50, 4.54 and 4.58). The unstandardized factor loadings for all the measured models had p-values of < 0.001, showing the latent constructs of the measured models were statistically significant (Table 4.43, 4.47, 4.51, 4.55 and 4.59). All these indicate that the results thereof will have significant explanatory power on the models.

CMV and CLFD were used to check for spurious correlations between variables as a result of using similar measurement methods for the variables. CMV yielded results of 0.0009, 0.0000, 0.0009 and 0.0016 (Figure 4.16 – 4.19) which were < 0.5. CLFD showed the difference in standardized weights with and without common latent factor. These figures varied between -0.018 and 0.177 (Table 4.62 – 4.65) indicating they were < 0.2. The results of the CMV and CLFD confirm that the models were not affected by spurious correlations.

CHAPTER FIVE: TEST OF HYPOTHESES, INTERPRETATIONS AND DISCUSSIONS

5.1 Introduction

This study sought to examine the relationships among reverse logistics, process innovation, operational performance and competitive advantage of manufacturing firms in Kenya. Five hypotheses were tested and section 5.2 provides the discussion of findings from the test of hypothesis. Section 5.3 provides comparative analysis between the expected relationships and the actual findings.

5.2 Tests of Hypotheses

To achieve the objectives of the study, hypotheses were tested and the results and discussions of findings for each of the five hypotheses are provided in the ensuing sub-sections.

5.2.1 The Influence of Reverse Logistics on Competitive Advantage of Manufacturing Firms in Kenya

The first objective of this study was to establish the influence of reverse logistics on competitive advantage of manufacturing firms in Kenya. A review of literature suggested that reverse logistics can be implemented using four strategies. For this objective, the study hypothesized that;

H1: Reverse logistics has no significant influence on a firm's competitive advantage.

Indices advanced by Hair et al., (2014) such as chi-square, RMSEA, GFI, AGFI, CFI, NFI, TLI and CMIN/DF were used in examining model fitness. These had values of 49.099, 0.117, 0.929, 0.841, 0.989, 0.983, 0.980 and 3.069 respectively indicating a good model fit (Table 4.42).

Figure 4.7 revealed the standardized structural equation model for the reverse logistics interaction with competitive advantage as predictor and outcome variables respectively. From the figure the path co-efficient between reverse logistics and competitive advantage was positive (0.66) showing that the reverse logistics association with competitive advantage was positive. Figure 4.6 reveals the unstandardized structural equation model for reverse logistics interaction with competitive advantage with a path co-efficient of 5.25 meaning that for every unit increase in reverse logistics initiatives competitive advantage improves by a factor of 5.25. The p-value for reverse logistics interaction with competitive advantage was < 0.001 (table 4.45). Since this p-value was < 0.05, the null hypothesis was rejected therefore reverse logistics has a significant and positive influence on a firm's competitive advantage.

5.2.2 The Mediation Effect of Operational Performance on Reverse Logistics Association with Competitive Advantage in Manufacturing Firms in Kenya

The second objective of this study was to determine the influence of operational performance on the association linking reverse logistics with competitive advantage of manufacturing firms in Kenya. For this objective, the study hypothesized that;

H2: Operational performance had no significant mediating influence on the relationship between reverse logistics and a firm's competitive advantage.

For one to identify the mediating effect, it was important to establish whether significant interaction exists between the predictor and outcome variable. Once the nature of the association was identified the mediator was introduced in the diagram to assess the indirect effect on the association between the predictor and outcome variables. Before testing for mediation, model fit was assessed using chi-square, RMSEA, GFI, AGFI, CFI, NFI, TLI and CMIN/DF. These had values of 201.009, 0.154, 0.827, 0.694, 0.962, 0.952, 0.943 and 4.568 respectively indicating a fairly good model fit (Table 4.46).

The direct interaction of reverse logistics on competitive advantage was found to be significant as discussed in section 5.2.1 above. For the indirect relationship, Figure 4.9 revealed the standardized structural equation model for the association linking reverse logistics, competitive advantage and operational performance as independent, dependent and mediating variables respectively. From the figure the path co-efficient between reverse logistics and competitive advantage was positive (0.02) having significantly decreased as compared to the direct relationship (0.66). The figure also revealed that the path co-efficient between reverse logistics and operational performance and between operational performance and competitive advantage were 0.69 and 0.92 respectively.

Figure 4.8 revealed the unstandardized structural equation model for reverse logistics association with competitive advantage with a path co-efficient of 0.17 a decrease of 5.08 as compared to the direct relationship. The p-value for the reverse logistics association with competitive advantage was < 0.001 for the direct relationship but changed to 0.670 in the mediating relationship, while the p-value between reverse logistics and operational performance and between operational performance and competitive advantage were both <

0.001 (table 4.49). Since these p-value were both < 0.05, the null hypothesis was rejected therefore operational performance had significant mediating influence on the relationship between reverse logistics and a firm's competitive advantage.

5.2.3 The Moderation Effect of Process Innovation on the Association linking Reverse Logistics and Operational Performance of Manufacturing Firms in Kenya

The third objective of this study was to determine the influence of process innovation on the relationship between reverse logistics and operational performance of manufacturing firms in Kenya. For this objective, the study hypothesized that;

H3: Process Innovation has no significant moderating influence on the relationship between reverse logistics and operational performance.

According to Sharma, Durand and Gur-Arie (1981) in order to identify the moderating effect requires the creation of an interaction variable. The interaction variable was found by computing the product of reverse logistics and process innovation for each data point in the respective data sets. This resulted in the unstandardized path diagram shown in figure 4.10. The model fit was assessed using chi-square, RMSEA, GFI, AGFI, CFI, NFI, TLI and CMIN/DF (Hair et al., 2014). These had values of 183.970, 0.120, 0.848, 0.761, 0.970, 0.957, 0.960 and 3.172 respectively indicating a good model fit (Table 4.50).

Based on figure 4.11 the path co-efficient for the interaction variable was positive (0.07) indicating the process innovation had a positive moderating effect on the association linking reverse logistics and operational performance. The p-values between reverse logistics, process innovation and the interaction variable were <0.001, 0.005 and 0.006 (table 4.53). Since the p-value between the interaction variable, process innovation and reverse logistics were < 0.05, this indicated the moderating effect is statistically significant. The null hypothesis was rejected and a conclusion that process innovation has significant moderating effect on the relationship between reverse logistics and operational performance reached.

5.2.4 The Moderated - Mediation Effect of Process Innovation and Operational Performance

The fourth objective of this study was to determine the conditional indirect effect of process innovation and operational performance on the reverse logistics association with competitive advantage of manufacturing firms in Kenya. For this objective, the study hypothesized that;

H4: Process Innovation and operational performance have no significant moderated-mediation influence on the relationship between reverse logistics and competitive advantage.

Model fit was assessed using chi-square, RMSEA, GFI, AGFI, CFI, NFI, TLI and CMIN/DF. These had values of 665.019, 0.188, 0.743, 0.629, 0.907, 0.892, 0.881 and 6.274 respectively indicating a fairly good model fit (Table 4.54).

For the moderated-mediation relationship figure 4.13 revealed the standardized structural equation model with reverse logistics, process innovation, operational performance and competitive advantage as predictor, moderating, mediating and outcome variables respectively. From the figure the path co-efficient between reverse logistics and competitive advantage was positive (0.05) having significantly decreased as compared to the direct relationship (0.66) in figure 4.7. The figure also reveals that the path co-efficient between reverse logistics and the interaction variable and between operational performance and competitive advantage were 0.05 and 0.89 respectively.

Figure 4.13 revealed the path co-efficient for the interaction variable was positive (0.05) indicating the process innovation had a positive moderating relationship between reverse logistics and operational performance. The p-values between the reverse logistics, process innovation and the interaction variable were < 0.006 (table 4.57) therefore the relationship was statistically significant.

Figure 4.12 reveals the unstandardized structural equation model for reverse logistics interaction with competitive advantage with a path co-efficient of 0.38 a decrease of 4.87 as compared to the direct relationship in figure 4.6. While the p-value between the latent variables of reverse logistics and competitive advantage was < 0.001 in the direct relationship (table 4.45), the p-value for the reverse logistics interaction with competitive advantage was 0.334 in the moderated-mediation relationship. The p-value between reverse logistics and operational performance was 0.420 and between operational performance and competitive advantage was < 0.001. The p-values between reverse logistics and the interaction variable was 0.006 and between process innovation and the interaction variable was 0.005 (table 4.57).

Since the p-value for the reverse logistics interaction with competitive advantage was > 0.05, the p-value between reverse logistics and operational performance > 0.05, the p-value between reverse logistics and the interaction variable < 0.05, the p-value between process innovation and the interaction variable < 0.05 and between operational performance and competitive advantage was < 0.05 the null hypothesis was rejected and process innovation and operational performance were found to have a significant partial moderated-mediation influence on the reverse logistics association with competitive advantage.

5.2.5 The Joint Effect of Reverse Logistics, Process Innovation and Operational Performance on Competitive Advantage of Manufacturing Firms in Kenya

The fifth objective of this study was to examine the joint effect of reverse logistics, process innovation and operational performance on competitive advantage of manufacturing firms in Kenya. For this objective, the study hypothesized that;

H5: Reverse logistics, process innovation and operational performance had no significant joint influence on a firm's competitive advantage.

Model fit was assessed using chi-square, RMSEA, GFI, AGFI, CFI, NFI, TLI and CMIN/DF. These had values of 547.531, 0.202, 0.747, 0.583, 0.904, 0.890, 0.877 and 5.824 respectively indicating a fairly good model fit (Table 4.58).

For the joint relationship, Figure 4.15 reveals the standardized structural equation model for the relationship between reverse logistics, process innovation, operational performance as predictor variables and competitive advantage as the outcome variable. From the figure the path co-efficient between reverse logistics and competitive advantage was – 2.45. The figure also shows that the path co-efficient between process innovation and competitive advantage as 2.46 and between operational performance and competitive advantage were 0.95. The p-values between the reverse logistics, process innovation and operational performance on competitive advantage were 0.468, 0.462 and < 0.001 respectively (table 4.61) suggesting that only the relationship between operational performance and competitive advantage was statistically significant in the joint model. It is important to note the p-value between the latent variables of reverse logistics and competitive advantage was < 0.001 in the direct relationship (table 4.45).

Figure 4.14 reveals the unstandardized structural equation model for the reverse logistics interaction with competitive advantage with a path co-efficient of -19.34, that between process innovation and competitive advantage with a co-efficient of 20.12 and between operational performance and competitive advantage with a co-efficient of 0.84. Since only the p-value for the relationship between operational performance and competitive advantage was < 0.05, the null hypothesis is not rejected and conclude reverse logistics, process innovation and operational performance had no significant joint influence on a firm's competitive advantage.

5.2.6 Summary Table of Hypotheses Tests

Table 5.1 below provides a summary of the results from the hypothesis tests conducted in this study and the conclusions made thereof.

Table 5.1 ***Hypotheses Tests, Results and Conclusions***

Objective	Hypothesis	Results	Conclusion

Objective 1: To establish the influence of reverse logistics on competitive advantage.	H1: Reverse logistics has no significant influence on a firm's competitive advantage.	Reject	Significant
Objective 2: To determine the influence of operational performance on the relationship between reverse logistics and a firm's competitive advantage.	H2: Operational performance has no significant mediating influence on the relationship between reverse logistics and a firm's competitive advantage.	Reject	Significant
Objective 3: To determine the influence of process innovation on the relationship between reverse logistics and operational performance.	H3: Process innovation has no significant moderating influence on the relationship between reverse logistics and operational performance.	Reject	Significant
Objective 4: To examine the conditional indirect effect on the relationship among reverse logistics, process innovation and operational performance on a firm's competitive advantage.	H4: Process innovation and operational performance have no significant moderated-mediation influence on the relationship between reverse logistics and a firm's competitive advantage.	Reject	Significant
Objective 5: To examine the joint effect of reverse logistics, process innovation and operational performance on a firm's competitive advantage.	H5: Reverse logistics, process innovation and operational performance have no significant joint influence on a firm's competitive advantage.	Fail to reject	Not significant

Based on the above findings, the revised conceptual framework from the results is presented in the following figure 5.1.

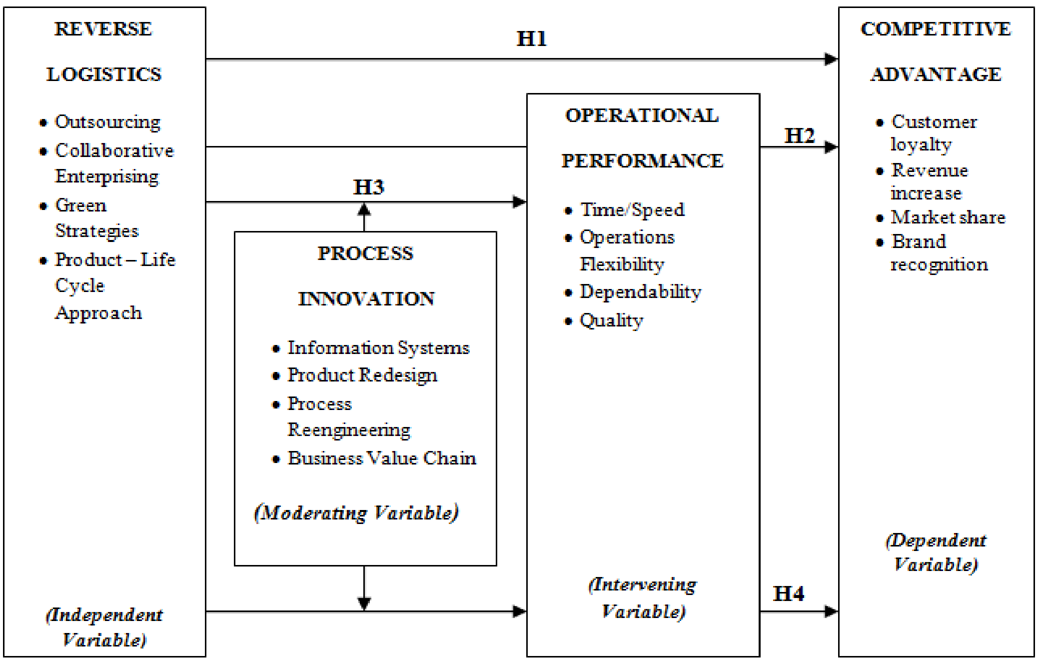


Figure 5.1. **Revised Conceptual Model**

From figure 5.1 above the fifth hypothesis where reverse logistics, process innovation and operational performance were hypothesized to have a joint effect on competitive advantage was deleted from the model. This is because the results demonstrated an insignificant relationship among the variables. Similarly, waste reduction was deleted as a construct to measure competitive advantage because of its low standardized factor loading according to figure 4.2. In addition, per unit cost was deleted as a construct to measure operational performance because of its low standardized factor loading according to figure 4.3. Finally, resource deployment was deleted as a construct to measure process innovation because of its low standardized factor loading according to figure 4.4.

5.3 Discussion of the Results

This section provided a discussion of the results of the study based on the five hypotheses. The discussion was as a result of a comparison of the results with the results of other similar studies.

5.3.1 Reverse Logistics and Competitive Advantage

From the results in the first hypothesis, reverse logistics had a significant and positive influence on a firm's competitive advantage. While observing that implementation of reverse logistics is intricate as a result of process challenges and unpredictability, Markley and Davis (2007) opined that reverse logistics can lead to gaining competitive advantage. Other studies have had similar conclusions to this empirical investigation (Glenn-Richey et al., 2005; Jim & Cheng, 2006; Jayaraman & Luo, 2007). In this regard the study has supported in reducing the uncertainty associated with past studies that have suggested contradicting findings on whether pursuing reverse logistics is beneficial or not to a firm

(Jim & Cheng, 2006; Abdulrahman et al., 2014). This has resulted to the expansion of literature supporting positive links between reverse logistics and competitive advantage.

Similarly, previous studies discussed reverse logistics as a unitary approach to the implementation of reverse flow systems (Ochieng et al., 2016). In this study reverse logistics was considered as an intervention consisting of several approaches. The strategies for the implementation of reverse logistics programmes included; Outsourcing which facilitated firms to concentrate on their core competences also enabled organizations to achieve higher degrees of flexibility and they were able to transfer risk to third party (He & Wang, 2005; Moghaddam, 2015; Hsu et al., 2016). Collaborations among supply chain partners facilitated the integration of reverse logistics operations for firms in an industry (Hung-Lau & Wang, 2009). Adopting green strategies such as reuse, recycle and remanufacture helped in "greening" the supply chain (Rogers & Tibben-Lembke, 2001; Rao & Holt, 2005). Finally, implementing reverse logistics using the product-life cycle approach allowed for recreation of value through the closed-loop supply chain (Closs et al., 2011; Govindan et al., 2015; Sangwan, 2017).

This study also made additional contribution to the knowledge base of reverse logistics by considering the variable as an independent latent variable. Previous studies discussed reverse logistics as a sub-variable of Green Supply Chain Management (GSCM) practices (Zhu et al., 2008; Ninlawan et al., 2010; Ochieng et al., 2016). In the production of goods and services, organizations today are faced with increasing need to conserve the environment through reverse logistics programmes while creating competitiveness (Markley & Davis, 2007; Kumar & Putnam, 2008; Kwateng et al., 2014). This study considered reverse logistics independently from other latent variables as a means to address key concerns of reverse logistics namely; lowered product quality; increased need for liberal returns policies; increased change in buyer's tests and preferences; increased internet product purchase and shortened product life cycles (Bernon & Cullen, 2007; Ravi & Shankar, 2015).

Reverse logistics association with competitive advantage was anchored on the transaction cost theory and resource advantage theory of competition which suggest that competitive advantage is gained by firms that offer distinct value proposition using customized value chains with unique trade-offs from those of their competitors. In so doing this study took a holistic view of competitive advantage by lending traction to Markley & Davis (2007) who suggested that competitive advantage can be measured through customer loyalty, revenue increase, market share and brand recognition.

5.3.2 Reverse Logistics, Operational Performance and Competitive Advantage

Theoretical underpinning from the resource advantage theory of competition and literature review led to the opinion that operational performance mediates the association linking reverse logistics implementation and firms gaining competitive advantage. The result in the second hypothesis indicated there was complete mediation of operational performance on reverse logistics association with competitive advantage.

This result is in congruence with the results from other studies (Prakash & Barua, 2015; Cannella et al., 2016; Dias & Braga Jr., 2016). These studies generally assumed that mobilizing resources in a unique way led to the creation of comparative advantage which in turn resulted in the creation of competitive advantage but with minimal empirical confirmation. This study therefore made a positive contribution to the link between reverse logistics programme achievement, gaining operational competence and the achievement of competitive advantage.

The theoretical basis behind the mediation relationship between reverse logistics, operational performance and competitive advantage was founded on the resource advantage theory of competition. The theory posited that, harnessing unique resources assists firms to gain unique internal competencies, which enable firms' to build competitive advantage at the marketplace (Barney, 1991). The study revealed that there exists a positive and significant association linking reverse logistics implementation and operational performance in creating competitive advantage. This supported the proposition that the resource selection process determines how competition for comparative advantage is gained (Conner, 1991; Hunt & Morgan, 2005).

5.3.3 Reverse Logistics, Operational Performance and Competitive Advantage

From the results in the third hypothesis, process innovation had significant moderating influence 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 generate sustainability creating processes. According to Armbruster et al. (2008), innovations influence operational performance dimensions such as flexibility, dependability, productivity and quality. This study, revealed that developing innovative reverse logistics capabilities using resources was going to improve operational performance and competitiveness (Huang and Yang, 2014; Glenn-Richey et al., 2005; Hsu et al., 2016).

These findings 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 however agree with those of Rogers (1976) that not all innovations yield positive results and should not be wholesomely adopted. They further concur 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.

5.3.4 Moderated – Mediation effect of Process Innovation and Operational Performance on Reverse Logistics and Competitive Advantage

The results in the fourth hypothesis indicate there was significant partial moderated-mediation effect of process innovation and operational performance on the relationship between reverse logistics and a firm's competitive advantage.

The partial moderated- mediation effect has been supported by empirical literature. Studies suggested a reverse logistics interaction with competitive advantage (Hung-Lau & Wang, 2009; Jim & Cheng, 2006; Prakash & Barua, 2015). Further empirical literature showed a relationship among reverse logistics, process innovation and operational performance (Christmann, 2000; Huang & Yang, 2014; Morgan et al. 2016). Literature also linked reverse logistics, operational performance and competitive advantage (Jack et al., 2010; Russo & Cardinali, 2012; Cannella et al., 2016). This study therefore made a positive contribution to the nature of the relationship among reverse logistics programme achievement, process innovation, gaining operational capabilities and gaining competitive advantage.

The over-arching theory in this study was the institutional theory which viewed the structure of the firm as built on technology, resource dependencies and institutional forces (Scott, 2008). Huang and Yang (2014) argued that a firm's response to institutional pressures affected how reverse logistics and external organizational performance related. Institutions determine interactions among people using an informal process governed by codes of conduct, behavior norms and conventions and their enforcement characteristics (North, 1991). This study revealed that there was a significant association among reverse logistics implementation, process innovation and operational performance in creating competitive advantage. The study supported the proposition that for firms to compete increased organizational legitimacy should be as a result of coercive, mimetic and normative forces (Kostova, Roth & Dacin, 2008).

5.3.5 Joint Effect of Reverse Logistics, Process Innovation and Operational Performance on Competitive Advantage

From the fifth hypothesis, reverse logistics, process innovation and operational performance had no significant joint influence on a firm's competitive advantage. Only the association linking operational performance and competitive advantage was statistically significant in the joint model, despite the fact that the reverse logistics association with competitive advantage was statistically significant in the direct relationship (table 4.45).

This can be attributed to the complete mediation effect of operational performance on the reverse logistics interaction with competitive advantage and the significant moderating influence of process innovation on the association linking reverse logistics and operational performance. Studies conducted by Stock et al. (2006); Russo and Cardinali (2012); Prakash and Barua, (2015); Cannella et al. (2016) all do support that operational performance contributed to creating competitive advantage capabilities for firms'. The study demonstrated that, order fill rate, number of product lines, machine availability and lead-time influence competitive advantage.

CHAPTER SIX: SUMMARY, CONCLUSIONS, IMPLICATIONS AND RECOMMENDATIONS

6.1 Introduction

This chapter summarizes the findings and draws conclusions from the study. The chapter then proceeds to discuss how the findings and conclusions contribute to the study. The discussion on the contributions is done at the knowledge, theory, policy and practice level. Finally, the limitations of the study are discussed and probable future research streams arising from the study made.

6.2 Summary of Findings

This study hypothesized to establish how reverse logistics association with competitive advantage as inveigled by process innovation and operational performance among manufacturing firms in Kenya. Specifically, reverse logistics was the predictor variable and competitive advantage was the outcome variable. Operational performance mediated the association linking reverse logistics and creating competitiveness advantageously. Process innovation moderated the association linking reverse logistics and operational performance. Similarly the moderated-mediation effect of process innovation and operational performance on how reverse logistics generated competitive advantage were tested. Finally to understand these relationships further an analysis of the effect of reverse logistics, process innovation and operational performance as independent variables on competitive advantage was conducted.

The first objective was to establish the influence of reverse logistics on competitive advantage of manufacturing firms in Kenya. Model fit as summarized in table 4.42

suggested good model fit with chi-square, RMSEA, GFI, AGFI, CFI, NFI, TLI and CMIN/DF values of 49.099, 0.117, 0.929, 0.841, 0.989, 0.983, 0.980 and 3.069 respectively. From figure 4.7 the path co-efficient between reverse logistics and competitive advantage was positive (0.66) showing that reverse logistics association with competitive advantage was positive and moderately strong. The p-value for reverse logistics interaction with competitive advantage was < 0.001 (table 4.45) indicating a statistically significant relationship.

Determining the influence of operational performance on the association linking reverse logistics with competitive advantage in manufacturing firms in Kenya formed the second objective. Before testing for mediation, model fit was assessed using chi-square, RMSEA, GFI, AGFI, CFI, NFI, TLI and CMIN/DF. These had values of 201.009, 0.154, 0.827, 0.694, 0.962, 0.952, 0.943 and 4.568 respectively indicating a fairly good model fit (Table 4.46). From figure 4.9 the path co-efficient between reverse logistics and competitive advantage was positive (0.02) having significantly decreased as compared to the direct relationship (0.66). The figure also revealed that the path co-efficient between reverse logistics and operational performance and between operational performance and competitive advantage were 0.69 and 0.92 respectively. From table 4.49 the p-value between reverse logistics and operational performance and between operational performance and competitive advantage were both < 0.05 and the p-value for reverse logistics interaction with competitive advantage was > 0.05, this indicated there was complete mediation of operational performance on reverse logistics interaction with competitive advantage.

Determining the influence of process innovation on the association linking reverse logistics and operational performance of manufacturing firms in Kenya formed the third objective. Model fit results indicated chi-square, RMSEA, GFI, AGFI, CFI, NFI, TLI and CMIN/DF having values of 183.970, 0.120, 0.848, 0.761, 0.970, 0.957, 0.960 and 3.172 respectively indicating a good model fit (Table 4.50). From table 4.53, because the p-value between the interaction variable, process innovation and reverse logistics and were < 0.05, this indicated the moderating effect of process innovation on reverse logistics and operational performance was statistically significant.

Examining the conditional indirect effect of process innovation and operational performance on the association linking reverse logistics with competitive advantage among manufacturing firms in Kenya, was the fourth specific objective. Model fit indicated values of 665.019, 0.188, 0.743, 0.629, 0.907, 0.892, 0.881 and 6.274 for chi-square, RMSEA, GFI, AGFI, CFI, NFI, TLI and CMIN/DF respectively indicating a fairly good model fit (Table 4.54). Since the p-value (Table 4.57) for the reverse logistics association with competitive advantage was > 0.05, the p-value between reverse logistics and operational performance > 0.05 and between operational performance and competitive advantage was < 0.05 this indicated there was partial moderated-mediation of process innovation and operational performance on the association linking reverse logistics with competitive advantage.

The final objective examined the joint effect of reverse logistics, process innovation and operational performance on competitive advantage of manufacturing firms in Kenya. Model fit was assessed using chi-square, probability level, RMSEA, GFI, AGFI, CFI, NFI, TLI and CMIN/DF. These had values of 547.531, 0.202, 0.747, 0.583, 0.904, 0.890, 0.877 and 5.824 respectively indicating a fairly good model fit (Table 4.58). The p-values (Table 4.61) between the reverse logistics, process innovation and operational performance on competitive advantage were 0.468, 0.462 and < 0.001 respectively suggesting that only the association linking operational performance and competitive advantage was statistically significant in the joint model.

6.3 Conclusions

One key conclusion of this research is that implementation of reverse logistics holistically leads to competitive benefits in the form of increased customer loyalty, increased market share, improved brand recognition and an increase in revenues (Glenn-Richey et al., 2005; Jim & Cheng, 2006; Jayaraman & Luo, 2007). The positive association of reverse logistics and advantageously gaining competitiveness as demonstrated in the results of this study propounded that manufacturing firms in Kenya are cognizant of the importance of reverse logistics strategies in creating competitiveness. Further, reverse logistics programmes while creating competitiveness also need to preserve and conserve the environment in today's competitive markets (Markley & Davis, 2007; Kumar & Putnam, 2008; Kwateng et al., 2014).

A second conclusion is that operational performance strongly dominates the significant reverse logistics interaction with competitive advantage. This meant that when resources are mobilized in a unique way, they create comparative advantage which then has the outcome of creating competitive advantage (Prakash & Barua, 2015; Cannella et al., 2016; Dias & Braga Jr., 2016). This means that for manufacturing firms in Kenya the better the resource selection process the higher the chances of gaining competitiveness through the gains of comparative advantage (Conner, 1991; Hunt & Morgan, 2005). This reveals that gaining operational competence is linked to the achievement of competitive advantage.

The third conclusion is 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.

Considering there was complete mediation of operational performance on the association linking reverse logistics with operational performance, the moderation of process innovation had negative consequence to this relationship. This could be attributed to the strong dominance of operational performance on the reverse logistics association with competitive advantage and the fact that process innovation had significant influence on the relationship between reverse logistics and operational performance. This is further supported by the joint model where, only the association linking operational performance and competitive advantage was statistically significant among manufacturers in Kenya.

6.4 Implications of the Study

Although it is relevant to compare the results of this study with previous studies, an evaluation of the implications builds the basis for making improvements theoretically, empirically and practically. Therefore the findings contribute to knowledge, theory, policy and practice in the following ways as discussed in the subsections below.

6.4.1 Contribution to Knowledge

The findings propounded that reverse logistics influences competitive advantage in the direct-relationship. This is supported by general reverse logistics literature (Glenn-Richey et al., 2005; Jim & Cheng, 2006; Jayaraman & Luo, 2007). These results bridge the gap in knowledge by showing effective implementation of reverse logistics positively influences competitive advantage.

The study also observed that mobilization of resources in a distinctive way creates operations efficiency and this leads to achieving competitive advantage. This is propounded in literature (Prakash & Barua, 2015; Cannella et al., 2016; Dias & Braga Jr., 2016). Therefore the study contributes to knowledge by suggesting that the comparative advantage is improved by having a better resource selection process. This in turn improves competitiveness (Conner, 1991; Hunt & Morgan, 2005). This reveals that achievement of competitive advantage is dependent on gaining operational competence.

In this study, establishing innovative reverse logistics capabilities would result to improved operational performance (Ambruster et al., 2008; Huang and Yang, 2014; Hsu et al., 2016). The results build on the understanding that not all innovations yield positive results. This contributes to knowledge by emphasizing that adoption of innovation does not automatically result to improved internal performance for a firm. Secondly it also emphasizes that the extent to which an innovation will result to improved performance is as a result of the difference between how personal characteristics affect a system and how the system affects diffusion (Rogers, 2003). The research therefore confirms the limitations of causality and heterophily in the diffusion of innovation theory.

6.4.2 Contribution to Theory

This study was based on the transaction cost theory, resource advantage theory of competition, diffusion of innovations theory and institutional theory. The reverse logistics interaction with competitive advantage was anchored on the transaction cost theory and resource advantage theory of competition. These theories propound that competitive advantage is achieved by firms that offer distinguishable value proposition using custom-made value chains with unique trade-offs from those of their competitors. The research contributed to theory by supporting Markley & Davis (2007) who suggested that competitive advantage can be measured through customer loyalty, revenue increase, market share and brand recognition.

Theoretical foundation from the resource advantage theory of competition led to the assertion that operational performance mediates the reverse logistics association with competitive advantage. The theory posited that, mobilizing distinct resources enables firms to gain distinct internal competencies, which enable organizations to build competitive advantage at the marketplace (Barney, 1991). Similarly the study contributed to theory by supporting the assertion that the resource selection process determines how competition for comparative advantage is gained (Conner, 1991; Hunt & Morgan, 2005).

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).

This study contributed to the institutional theory by supporting the assertion that for firms to compete increased organizational legitimacy should be as a result of coercive, mimetic and normative forces (Kostova, Roth & Dacin, 2008). The study further demonstrated the significance of the institutional theory in comprehending the influence of technology, resource dependencies and institutional forces in the implementation of reverse logistics.

6.4.3 Contribution to Policy and Practice

These research findings directly impact policy and practice. The study provided a framework for regulating policy in the implementation of reverse logistics in achieving competitive advantage. The study suggested that by implementing reverse logistics as an integrated intervention this would lead to firms' increasing customer satisfaction levels, market share, brand recognition and also result to revenue increase. 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 results of the study also showed that only 17.9 percent of manufacturing firms in Kenya have sought ISO 14001 certification. This could be the fact that attributed to the fact that developing and implementing reverse logistics programmes is complex and requires additional capital and infrastructure (Rogers et al., 2002). Manufacturing firms in Kenya could also be lacking information systems and asset recovery systems to support informed decision making in implementing reverse logistics programmes (Dekker et al., 2013). The Kenyan manufacturing sector has also witnessed exploitation of the weak institutional mechanisms for enforcing environmental legislation (World Bank, 2016). These observations indicate that government laws and policies on the environment are important for reverse logistics implementation and environmental sustainability.

6.5 Recommendations

This study recognized that competitive advantage can be gained by implementing reverse logistics holistically. Therefore manufacturing firms should implement reverse logistics as an integrated intervention consisting of outsourcing, collaborative enterprising, green strategies and closed-loop supply chain approaches. By doing so, they will contribute to environmental conservation apart from gaining market share, customer satisfaction, brand recognition and an increase in revenues.

The study established that operational performance strongly influenced the reverse logistics link with competitive advantage. Manufacturing firms in Kenya should implement resource selection processes that increase the chances of gaining comparative advantage and hence competitiveness. This implementation should be guided by a process that requires identifying the uniqueness of resources the organization has and strategically placing these resources in a manner that builds comparative advantage.

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 using innovative processes. 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.

The study investigated the conditional indirect effect on the relationship among reverse logistics, process innovation and operational performance on a firm's competitive advantage. Process innovation was found to have negative consequence on the mediation relationship among reverse logistics, operational performance and a firm's competitiveness. This research recommends that future researchers should use the evidence-based framework that suggests the relationships underlying the research variables as a basis of building other relationships with reverse logistics. Therefore future reverse logistics studies could rely on this study in building upon the body of knowledge of reverse logistics.

6.6 Limitations of the Study

This study had limitations that could potentially provide key research themes for consideration by future researchers. First, although reverse logistics was considered as an integrated intervention consisting of a number of strategies (outsourcing, collaborative enterprising, green strategies and closed-loop supply chain) these strategies were not collectively exhaustive. Other strategies or approaches to the implementation of reverse logistics can provide additional explanation on how reverse logistics can be implemented more holistically. Additional strategies or approaches could also provide more explanations on the nature of causation of the independent variable on the other study variables.

Secondly, the study employed perceptual measures using Likert type scale in generating responses for reverse logistics and process innovation. Perceptual measures tend to vary with time and across different manufacturing sectors as was the case in this study. Objective data would have provided more robust results for the hypothesized relationships among the study variables. Future researchers should consider operationalizing variables in hypothesized relationships using direct measures of performance.

The third limitation was that this study used survey research design. The study did not therefore endavour to control for other factors affecting operational performance or competitive advantage in the hypothesized relationships in the context of manufacturing firms in Kenya. In order to fully account for the effect of reverse logistics, process innovation and operational performance on competitive advantage future researchers should consider experimental research design. Experimental research design focuses on designing research that has high internal validity.

The fourth limitation was that the response rate was rather low. Although covariance-based SEM was used in the data analysis, a higher number of responses would have provided more robust results. In using covariance-based SEM, future researchers should consider having more data points compared to this study.

6.7 Suggestions for Future Research

The factors 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 perceptual data. Objective data does not change over time and sectoral variations are easier to control within the models. Objective data therefore tends to have better explanatory power among the variables in the model. Future researchers should consider operationalizing variables in hypothesized relationships using direct measures of performance especially where covariance-based SEM is the method to be used for data analysis.

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.

Previously studies have indicated that developing process innovations when implementing reverse logistics, increased operational performance efficiency and competitiveness (Hart, 2005; Ambruster et al., 2008; Huang and Yang, 2014; Glenn-Richey et al., 2005; Hsu et al., 2016). The negative moderating consequence on the mediating relationship could be attributed to the long-term effect of process innovation on the association linking reverse logistics and operational performance. Further research is therefore relevant to ascertain the differences in the results.

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APPENDICES:

Appendix 1: Data Collection Instrument (Questionnaire):

Introduction:

Dear respondent,

This is a questionnaire designed to collect data on Reverse Logistics, Process Innovation, Operational Performance and Competitive Advantage of Large Manufacturing Firms in Kenya. The questionnaire has five main parts. Kindly respond to each of the items in the questionnaire. There are no wrong or right answers and the results are strictly confidential and purely for academic use. Your accurate participation will be crucial in attaining the objectives of the study.

PART A: ORGANIZATION PROFILE

Please answer all of the following questions. Where there is a choice indicate your answer with a tick (√) in the brackets ( ) or space provided.

1.1 Name of the organization

____

____

1.2 Designation of the respondent

____

1.3 The year the organization was established ________________________________

1.4 Is your organization ISO 14001 certified? Yes [ ] No [ ]

1.5 Which manufacturing sub-sector does your firm belong to?

Building, Mining and Construction
Food & Beverage Sector
Fresh Produce
Chemical and Allied Sector
Energy, Electrical and Electronics
Leather and Footwear
Metal and Allied Sector
Motor Vehicle and Accessories
Paper and Board Sector
Pharmaceutical and Medical Equipment
Plastics and Rubber
Textiles and Apparels
Timber, Wood and Furniture

PART B: REVERSE LOGISTICS

2.1 Please record the degree to which your organization concurs with the statements regarding reverse logistics. Please read each statement carefully and tick (√) the appropriate box (Key: 1 = Not at all; 2= To a small degree; 3= To a moderate degree; 4= To a large degree; and 5 = To a very large degree).

Label	Reverse Logistics	1	2	3	4	5
	Outsourcing Reverse Logistics					
OS1	Outsourcing reverse logistics increases return on investment					
OS2	Outsourcing reverse logistics provides better operational flexibility					
OS3	Outsourcing reverse logistics results to improved customer service quality					
OS4	Outsourcing reverse logistics results to improved speed to market.					
OS5	Reverse logistics outsourcing provides access to functional and industry expertise					
OS6	Reverse logistics outsourcing provides access to best technology					
OS7	Reverse logistics outsourcing results to benefitting from best practices					
OS8	In-housing reverse logistics is more costly than outsourcing					
	Collaborative Enterprising in Reverse Logistics					
CE1	There is high volume data exchange among partners in reverse logistics.					
CE2	Partners implementing reverse logistics have standardized information exchange platforms					
CE3	The focus in implementing reverse logistics is on building data integrity among supply chain partners					
CE4	The emphasis in implementing reverse logistics is on managing transactions using IT tools.					
CE5	Partners implementing reverse logistics participate in short-term planning and decision making among					
CE6	In implementing reverse logistics more interpersonal interactions and less transactional data is used					
CE7	Supply chain partners have fully integrated reverse logistics processes among themselves					
CE8	Partners have set joint business goals in planning and implementing reverse logistics					

CE9	Supply chain partners have designed inter-enterprise reverse logistics processes					
CE10	Supply chain partners have fully integrated reverse logistics processes among them.					
	Green Strategies in Reverse Logistics					
GS1	Awareness seminars for suppliers and contractors are conducted on green strategies					
GS2	Suppliers are guided in setting-up their own green programs.					
GS3	Suppliers are chosen based on the extent of implementation of green programs					
GS4	There is a structure for suppliers to share knowledge and issues in green implementation					
GS5	Suppliers are informed about the benefits of green programs					
GS6	Products are designed to facilitate re-use					
GS7	Products are designed to facilitate recycling					
GS8	Products are designed to facilitate remanufacture					
GS9	Organizational processes optimization leads to a reduction in emissions and solid waste					
GS10	Savings in energy and water are an outcome of using technologically cleaner processes					
GS11	Recycling of materials internally is practiced during production					
GS12	Supply chain partners practice environmental management principles like worker empowerment.					
GS13	Environmentally affable packaging such as eco-labeling is used					
GS14	Environmentally affable transportation is used					
GS15	Information on environmentally affable products is shared to consumers.					
	Product Life Cycle Approach					
PLA1	Control and reduction of returns rate does not undermine customer service					
PLA2	Supply chain partners segregate returned products into categories for processing, selling or disposal					
PLA3	The firm undertakes repair, remanufacture or refurbishing activities to make product reusable					
PLA4	The firm recycles returned product parts to be used in manufacture of other products or components					
PLA5	The firm undertakes disposal activities for returned products that have no more economic or ecological value					

PLA6	The firm facilitates transportation of returned products in the process of recovering value					

2.2 Using the scale below, please indicate the percentage to which you agree with the following statements regarding reverse logistics.

Label	**Reverse Logistics**	**0 - 10%**	**11 - 20%**	**21 - 30%**	**31 - 40%**	**Over 40%**
	Estimated cost of running reverse logistics operations in relation to sales					
	Estimated cost recovered from reverse logistics activities					
	Energy used in handling returns in relation to total energy consumption					
	Rate of product refurbishment in relation to total production					
	Rate of product remanufacture in relation to total production					
	Raw materials recycled					
	Raw materials moved to landfills, incinerated or disposed as waste					

PART C: PROCESS INNOVATION

3.1 Please record the degree to which your organization concurs with the statements regarding process innovation. Please read each statement carefully and tick (√) the appropriate box (Key: 1 = Not at all; 2= To a small degree; 3= To a moderate degree; 4= To a large degree; and 5 = To a very large degree).

Label	**Process Innovation**	**1**	**2**	**3**	**4**	**5**
	Information Systems (IS)					
IS1	Information systems in use are perceived to be better than our competitors.					
IS2	Information systems in use are perceived to be better than previous systems in use.					
IS3	Information systems in use are perceived as easy to learn, understand and use.					

IS4	Information systems in use are perceived as being compatible to the needs of potential users.					
IS5	Users consider the information systems as easy to explore and experiment with.					
IS6	The results of using the information systems in the organization are visible.					
	Resource Deployment					
RD1	Firm budgets have a component for reverse logistics activities					
RD2	Staff have relevant skills to implement reverse logistics activities					
RD3	Supply chain partners have acquired the relevant technology and equipment to implement reverse logistics					
RD4	Customers are integrated in our current reverse logistics programming					
RD5	Suppliers are integrated in our current reverse logistics programming					
RD6	Resource deployment processes in the firm are perceived to be superior to our competitors					
RD7	Over time resource deployment processes in the organization have improved					
	Product Redesign					
PRD1	New markets and market segments can be attributed to product redesign					
PRD2	The firm maintains superiority in manufacturing technology					
PRD3	Change in customer requirements have influenced our product design strategy					
PRD4	Clients consider our current products as more convenient to use					
PRD5	Over time manufacturing processes have been standardized and simplified					
PRD6	Manufacturing processes are much easier as a result of redesigning our products					
PRD7	The benefits of product redesign processes can be quantified within the organization.					
PRD8	The quality of our products has improved as a result of product redesign					
	Process Reengineering					
PRE1	The vision of the organization is shared to all members of staff					

PRE2	Open communication among managers, supervisors and staff is encouraged					
PRE3	Staff members are accorded adequate information sharing platforms to facilitate their work					
PRE4	Management constructively use ideas from other staff members					
PRE5	Affable interactions among staff exist					
PRE6	A teamwork approach is used in problem solving					
PRE7	Members of staff work together collegially					
PRE8	Performance measurement is in consonance with work systems					
PRE9	Performance reward systems adjust to conform with any work system changes					
PRE10	Employees have a degree of autonomy to make decisions					
PRE11	Employee skills updates training programs exist					
PRE12	Integration of functions in the organization is heavily dependent on information technology					
PRE13	Sufficient communication channels exist to transmit information					
	Business Value Chain					
BVA1	There is materials/component commonality with suppliers					
BVA2	Planning systems are adaptable to changes in the external environment					
BVA3	Suppliers have capacity to meet demand variability					
BVA4	Suppliers have a fairly constant lead-time variability					
BVA5	Suppliers voluntarily share information					
BVA6	Suppliers have adequate information and communication sharing infrastructure					
BVA7	Clients avail information on demand well in advance					
BVA8	Organizational systems have capacity to meet our customers demand variability					
BVA9	Customers voluntarily share information					

3.2 Using the scale below, please indicate the percentage to which you agree with the following statements regarding process innovation.

Label	Process Innovation	0-10%	11-20%	21-30%	31-40%	Over 40%
	Percentage of sales from new products introduced in the last two years					
	Percentage of budget devoted to research and development					
	Percentage of employee hours spent on research and ideation					
	Percentage of employees who have received training and tools for innovation.					

PART D: OPERATIONAL PERFORMANCE

4.1 Please record the number for the indicators of operational performance in your firm for the year 2015, 2016 and 2017.

Label	Operational Performance Indicator	Unit of Measure	2015	2016	2017
	Cost	Annual total variable cost of production			
		Total number of items produced in the year			
	Quality	Number of items ordered by customers in the year			
		Number of items actually delivered to customers in the year			
		Number of customer complaints in the year			
	Flexibility	Number of product lines in the year			
	Dependability	Number of hours equipment / machines are supposed to be			

		available for manufacturing operations in the year.			
		Number of hours equipment / machines were available for manufacturing operations in the year.			
	Delivery speed	Average number of days between when an order is received and when it is shipped to the customer in the year.			

PART E: COMPETITIVE ADVANTAGE

5.1 Please record the number for the indicators of competitive advantage in your firm for the year 2015, 2016 and 2017.

Label	Competitive Advantage Indicator	Unit of Measure	2015	2016	2017
	Customer loyalty	Number of customers at the beginning of the year			
		Number of customers acquired during year			
		Number of customers at the end of the year			
	Market share	Market share at the beginning of the year			
		Market share at the end of the year			

	Brand recognition	Cost of goods sold in the year			
		Total sales for the year			
	Waste reduction	No. of units tested for defects in the year			
		No. of units actually found to be defective in the year			
	Revenue increase	Percentage revenue increase for the year			

THANK YOU VERY MUCH FOR TAKING PART IN THIS PROCESS

Appendix 2: Quantum Index of Manufacturing Production (2012 – 2016)

Manufacturing Sector	2012	2013	2014	2015	2016*	% Change 2016
Food Products	116.6	126.3	132.5	134.5	143.2	6.5
Beverages and Tobacco	123.8	113.7	116.5	138.5	141.1	1.8
Textiles	117.7	112.1	113.9	129.9	130.3	0.3
Wearing Apparel	140,7	154.4	172.9	196.8	230.6	17.2
Leather and Related Products	130.9	135.4	118.6	103.5	111.2	7.5
Wood and Products of Wood	107.0	113.9	132.4	138.5	121.9	-12.0
Paper and Paper Products	135.2	144.9	140.1	140.3	152.6	8.7
Printing and Production of Recorded Media	100.2	102.3	99.3	99.2	99.2	0.0
Refined Petroleum Products	91.4	47.0	0.0	0.0	0.0	0.0
Chemical and Chemical Products	116.1	112.6	125.3	134.6	136.5	1.4
Pharmaceutical Products	189.4	250.0	295.9	362.8	416.0	14.7
Rubber & Plastic Products	110.9	111.8	118.6	130.7	137.6	5.2
Other Non-metalic Mineral Products	125.3	135.1	156.1	169.9	179.5	5.7
Basic Metals	124.2	149.8	152.7	150.9	169.7	12.5
Fabricated Metal Products	131.7	154.3	175.1	163.8	147.8	-9.8
Electrical Equipment	124.8	133.3	145.1	154.6	159.9	3.5
Machinery and Equipment	89.7	90.8	77.1	42.6	37.7	-11.6
Motor Vehicles, Trailers and Semi – Trailers	123.8	131.0	161.4	171.0	125.2	-26.7
Manufacture of Furniture	164.2	183.8	211.0	258.5	259.8	0.5
Other Manufacturing	134.7	139.5	174.6	210.1	211.8	0.8
Repair and Installation of Machinery and Equipment	106.8	110.2	117.8	122.0	122.0	0.0
Total Manufacturing	122.2	130.6	139.0	146.5	153.7	4.9

Source: KNBS, 2017.

Appendix 3: Manufacturing Firms Per Sub Sector

Sector	Number of Members	Proportionate Stratified Sample Size	Percentage Membership
Building, Mining and Construction	39	15	4.32%
Food & Beverage Sector	234	88	25.91%
Fresh Produce	13	5	1.44%
Chemical and Allied Sector	90	34	9.97%
Energy, Electrical and Electronics	58	22	6.43%
Leather and Footwear	9	3	1.00%
Metal and Allied Sector	96	36	10.63%
Motor Vehicle and Accessories	59	22	6.53%
Paper and Board Sector	82	31	9.08%
Pharmaceutical and Medical Equipment	30	11	3.32%
Plastics and Rubber	90	34	9.97%
Textiles and Apparels	73	28	8.08%
Timber, Wood and Furniture	30	11	3.32%
	903	340	100.00%

Source: KAM, 2018

Appendix 4: Sampled Firms Per Manufacturing Sub-Sectors

Building Mining and Construction:

1. Bamburi Cement Ltd
2. Building Construction Concepts
3. Flamingo Tiles (Kenya) Ltd
4. International Energy Technik Ltd
5. Kemu Salt Packers Production Ltd
6. Kurawa Industries Ltd
7. Malindi Salt Works
8. Mombasa Cement Ltd
9. Orbit Enterprises Ltd
10. Reliable Concrete Works Ltd
11. Saj Ceramics Ltd
12. Savannah Cement Ltd
13. Skylark Construction Ltd
14. Tile & Carpet Centre Ltd
15. Vallem Construction Ltd

Food and Beverage Sector:

1. Africa Spirits Ltd
2. Agriner Agricultural Development
3. Alliance One Tobacco Kenya Ltd
4. Alpha Fine Foods Ltd
5. Alpine Coolers Ltd
6. Aquamist Ltd
7. Aviano East Africa Ltd
8. Belat Enterprises
9. Beverage Services (K) Ltd
10. Bdelo Ltd
11. Broadway Bakery Ltd
12. Brown Biashara Ltd
13. Burton and Mamber Company Ltd
14. Czarnikow Sugar East Africa ltd
15. Caffe Del Duca Ltd
16. Capwell Industries Ltd
17. Chemelil Sugar Company Ltd
18. Coast Silos (K) Ltd
19. Coastal Bottlers Ltd
20. CoffTea Agencies Ltd
21. Del Monte Kenya Ltd
22. Diamond Industries Ltd
23. Doinyo Lessos Creameries Ltd
24. East African Breweries Ltd
25. East African Seed Co. Ltd
26. Eldoret Grains Ltd
27. Equator Bottlers Ltd
28. Excel Chemicals Ltd
29. Fresh Produce Exporters Association of Kenya
30. General Mills East Africa Ltd
31. Glacier Products (Amor Mia, Dairyland, Mio)
32. Global Tea and Commodities (K) Ltd
33. Gold Crown Foods (EPZ) Ltd
34. Golden Africa Kenya Ltd
35. Grain Industries Ltd
36. Heritage Foods Kenya Ltd
37. Highlands Mineral Water Company Ltd
38. Italian Gelati and Food Produce Ltd
39. Jjasm Mini-Distillery
40. Kabianga Dairy Ltd
41. Kambu Distillers Ltd
42. Karirana Estate Ltd
43. Kenafric Bakery
44. Kenchic Ltd
45. Kentaste Products Ltd
46. Kibos Sugar Refinery Ltd
47. Kenya Seed Company Ltd
48. Kenya Highland Seed Company Ltd
49. Kenya Horticultural Exporters (1977)
50. Kenya Sweets Ltd
51. Kenya Tea Growers Association
52. Kinangop Dairy Ltd
53. Koba Waters Ltd/Bromhill Springs Water
54. Kuguru Food Complex Ltd
55. Kwale International Company Ltd
56. Meru Water and Sewerage Services
57. Miritini Kenya Ltd
58. Mombasa Maize Millers
59. Mount Kenya Bottlers Ltd
60. Mzuri Sweets Ltd
61. Nairobi Flour Mills Ltd
62. NesFoods Industries Ltd
63. Norda Industries Ltd
64. Olivado EPZ
65. Pearly LLP
66. Pembe Flour Mills Ltd
67. Premier Flour Mills Ltd
68. Pride Industries Ltd
69. Pristine International Ltd
70. Promasidor Kenya Ltd
71. Propack Kenya Ltd
72. Pwani Oil Product Ltd

73. Rift Valley Bottlers Ltd
74. Scrumptious Eats Ltd
75. Sky Foods
76. South Nyanza Sugar Company Ltd
77. Sunny Processors Ltd
78. Supa Sweets Ltd
79. Tropikal Brand (Afrika) Ltd
80. T.S.S. Grain Millers Ltd
81. Umoja Flour Mills Ltd
82. United Distillers and Vintners
83. Valuepak Foods
84. Vert Ltd
85. Victory Farms Ltd 106 Thigiri Lane
86. West African Seasoning Co. Ltd
87. Winnie's Pure Health
88. Zeelandia East Africa Ltd

Fresh Produce:

1. Aquila Development Co. Ltd
2. Fontana Ltd
3. From Eden
4. Kankam Exporters
5. Rainforest Farmlands (K) Ltd

Chemical and Allied Sector:

1. Beierdorf East Africa Ltd
2. Buyline Industries Ltd
3. Canon Chemicals Ltd
4. Chrysal Africa Ltd
5. Cooper K-Brands Ltd
6. Crown Gases Ltd
7. Decase Chemicals Ltd
8. Diversey Eastern & Central Africa Ltd
9. Elex Products Ltd
10. Galaxy Paints & Coating Co. Ltd
11. Henkel Kenya Company Ltd
12. Hi-Tech Inks and Coatings
13. Interconsumer Products Ltd
14. Kaolin Crowners Company Ltd
15. KAPI Ltd
16. Ken Nat Ink & Chemicals Ltd
17. Maroo Polymers Ltd
18. MEA Ltd
19. Milly Glass Works Ltd
20. Murphy Chemicals Ltd
21. Orbit Products Africa Ltd
22. Osho Chemical Industries Ltd. (Kenya)
23. Procter & Gamble East Africa Ltd
24. PZ Cussons EA Ltd
25. Revolution Stores Ltd
26. Rutuba Bio Agri & Organic Fertilizers Co. Ltd
27. SC Johnson and Son Kenya
28. Shreeji Chemicals Ltd
29. Superfoam Ltd
30. Synresins Ltd
31. Tri-Clover Industries (K) Ltd
32. Twiga Chemical Industries Ltd
33. Vitafoam Products Ltd
34. Westminster Paints and Resins Ltd

Energy, Electricals & Electronics:

1. Asano International Ltd
2. Avery East Africa Ltd
3. Biogas Power Holdings (EA) Ltd
4. Daima Energy Services Ltd
5. Farm Refrigeration & Electrical Systems Ltd
6. Kenwest Cables Ltd
7. Libya Oil Kenya Ltd
8. Manufacturers & Suppliers (K) Ltd
9. Metlex International Ltd
10. Mustek East Africa Ltd
11. Oilzone (E.A) Ltd
12. Patronics Services Ltd
13. Phillips EA Ltd
14. Powerex Lubricants
15. Premier Solar Solutions Ltd
16. Repelectric (K) Ltd
17. Scales & Software (K) Ltd
18. Socabelec (EA) Ltd
19. Solimpexs Africa Ltd
20. Sollatek Electronics (Kenya) Ltd
21. Synergy-Pro
22. Vivo Energy Kenya Ltd

Leather & Footwear:

1. Azus Leather Ltd
2. Leather Industries of Kenya Ltd
3. Sandstorm Africa Ltd

Metal & Allied Sector:

1. African Marine & General Engineering Co. Ltd
2. Alloy Steel Casting Ltd
3. Arvind Engineering Ltd
4. Arshut Engineers Ltd
5. Blue Nile Wire Products Ltd
6. Brollo Kenya Ltd
7. Cook 'N Lite Ltd
8. Corugated Sheets Ltd
9. Davis & Shirtliff Ltd
10. Doshi & Company Hardware Ltd
11. East Africa Glassware Mart Ltd
12. Fine Engineering Works Ltd
13. Friendship Container Manufacturers Ltd
14. Greif Kenya Ltd
15. Heavy Engineering Ltd
16. Iron Art Ltd
17. Kenya General Industries Ltd
18. Kenya United Steel Company (2006) Ltd
19. Laminate Tube Industries Ltd
20. Marine Crafts & Boat Repairs
21. Mecol Ltd
22. Mitsubishi Corporation Nairobi Liaison Office
23. Naline Steel Works
24. Napro Industries Ltd
25. Orbit Engineering Ltd
26. Rolmil Kenya Ltd
27. Southern Engineering Co. Ltd
28. Standard Rolling Mills Ltd
29. Steelwool (Africa) Ltd
30. Tarmal Wire Products Ltd
31. Technoconstruct Kenya Ltd
32. Tononoka Rolling Mills Ltd
33. Towertech Africa Ltd
34. Viking Industries Ltd
35. Welding Alloys Ltd
36. Zenith Steel Fabricators Ltd

Motor Vehicles & Accessories:

1. Ace Motors Ltd
2. Associated Vehicle Assemblers Ltd
3. Autofine Filters & Seals Ltd
4. Bhachu Industries Ltd
5. Chui Auto Spring Industries Ltd
6. CMC Motors Group Ltd
7. Dodi Autotech (K) Ltd
8. General Motors East Africa Ltd
9. Igo Holdings Ltd
10. Kenya Vehicle Manufacturers Ltd
11. King-Bird (K) Ltd
12. Labh Singh Harnam Singh Ltd
13. Mash East Africa Ltd
14. Megh Cushion Industries Ltd
15. Pipe Manufacturers Ltd
16. Rockey Africa Ltd
17. Scania East Africa Ltd
18. Sohansons Ltd
19. Soroya Motors Spares
20. Toyota Tshusho East Africa Ltd
21. Transtrailers Ltd
22. Uni-Truck World Ltd

Paper and Board Sector:

1. Adpak International Ltd
2. ASL Packaging Ltd
3. Autolitho Ltd
4. Brand Printers LtdCempack Solutions Ltd
5. Colour Labels Ltd
6. De La Rue Currency and Security Print Ltd
7. Dodhia Packaging Ltd
8. East Africa Packaging Industries Ltd
9. Elegant Printing Works Ltd
10. English Press Ltd
11. Euro Packaging Ltd
12. Green Pencils Ltd
13. Guaca Stationers Ltd
14. Juja Pulp & Paper Ltd
15. Kenafric Diaries Manufacturers Ltd
16. Kenya Stationers Ltd
17. Kul Graphics Ltd
18. Manipal International Printing Press Ltd
19. Modern Lithographic (K) Ltd
20. Nation Media Group Ltd – Printing Plant
21. Ndalex Digital Technology
22. Paper House of Kenya Ltd
23. Prime Cartons Ltd
24. Printpak Multi Packaging Ltd
25. Ramco Printing Works Ltd
26. Shri Krishana Overseas Ltd
27. Sintel Security Print Solutions Ltd
28. Statpack Industries Ltd
29. The Print Exchange
30. Tissue Kenya Ltd

31. Uneeco Paper Products Ltd

Pharmaceuticals & Medical Equipment:

1. African Cotton Industries Ltd
2. Benmed Pharmaceuticals Ltd
3. Biodeal Laboratories Ltd
4. Cosmos Ltd
5. Dawa Ltd
6. Glaxo Smithkline Kenya Ltd
7. Laboratory & Allied Ltd
8. Osschemie (K) Ltd
9. Questa Care Ltd
10. Revital Healthcare (EPZ) Ltd
11. Universal Corporation Ltd

Plastic and Rubber:

1. ACME Containers Ltd
2. Afro Plastics (K) Ltd
3. Bobmil industries Ltd
4. Cocorico Investments Ltd
5. Dune Packaging Ltd
6. Elgitread (Kenya) Ltd
7. Five Star Industries Ltd
8. General Plastics Ltd
9. Jamlam Industries Ltd
10. Jumbo Chem Kenya Ltd
11. Kamba Manufacturing (1986) Ltd
12. Kentainers Ltd
13. Kinpash Enterprises Ltd
14. Lakhir Plastics Ltd
15. Mega (EA) Plastics
16. Mombasa Polythene Bags Ltd
17. Ombi Rubber Rollers Ltd

Textiles and Apparels:

18. Plast Packaging Industries Ltd
19. Plastic and Rubber Industries Ltd
20. Polyflex Industries Ltd
21. Polly Propelin Bags Ltd
22. Prosel Ltd
23. Raffia Bags (K) Ltd
24. Rushabh Industries Ltd
25. Sanpac Africa Ltd
26. Shiv Enterprises (E) Ltd
27. Silpack Industries Ltd
28. Sols Inclination Ltd
29. Smartpack Limited
30. Super Manufacturers Ltd
31. Thermopak Ltd
32. Treadsetters Tyres Ltd
33. Vectus Kenya Ltd
34. Zaverchand Punja Ltd

1. Adpack Ltd
2. Alpha Knits Ltd
3. Bedi Investments Ltd
4. Brilliant Garments EPZ Ltd
5. Ethical Fashion Artisons EPZ Ltd
6. Gone Fishing Ltd
7. Insight Kenya
8. Kavirondo Filments Ltd
9. Kenya Shirts Manufacturing Company Ltd
10. Kenya Trading (EPZ) Ltd
11. Kikoy Mall EPZ Ltd
12. Leeways Control Systems and Suppliers
13. Long-Yun Ltd
14. Manchester Outfitters
15. New Wide Garments (K) Ltd
16. Panah Ltd
17. Penny Galore Ltd
18. Rivatex (East Africa) Ltd
19. Shin-Ace Garments Kenya (EPZ) Ltd
20. Soko EPZ Ltd
21. Spin Knit Ltd
22. Spinners & Spinners Ltd
23. Squaredeal Uniforms Centre Ltd
24. Summit Fibres Ltd
25. Tarpo Industries Ltd
26. TSS Spinning and Weaving Ltd
27. United Aryan (EPZ) Ltd
28. World of Kikoys

Timber, Wood & Furniture:

1. Biashara Master Sawmills
2. Contrive Industries Ltd
3. Fine Wood Works Ltd
4. Furniture International Ltd
5. Little Cribs Ltd
6. Major Furniture

7. Panesar's Kenya Ltd
8. Rai Plywoods (Kenya) Ltd
9. Shamco Industries Ltd
10. Timsales Ltd
11. Wood Makers (K) Ltd

Source: KAM, 2018

Appendix 5: Inter-Item Correlation Matrix between Latent Constructs of Reverse Logistics and Process Innovation

	RLOS1	RLCE1	RLGS1	RLPLCA1	PIIS1	PIPRD1	PIPRE1	PIBVA1
RLOS1	1.000							
RLCE1	.991**	1.000						
RLGS1	.994**	.990**	1.000					
RLPLCA1	.620**	.613**	.639**	1.000				
PIIS1	.988**	.990**	.989**	.620**	1.000			
PIPRD1	.991**	.992**	.992**	.627**	.989**	1.000		
PIPRE1	.462**	.440**	.468**	.694**	.453**	.454**	1.000	
PIBVA1	.962**	.966**	.964**	.620**	.968**	.963**	.448**	1.000

**. Correlation is significant at the 0.01 level (2-tailed).

Appendix 6: Inter-Item Correlation Matrix between Latent Constructs of Reverse Logistics and Operational Performance

	RLOS1	RLCE1	RLGS1	RLPLCA1	OPOFR1	OPPL1	OPDMA1	OPLTA1
RLOS1	1.000							
RLCE1	.991**	1.000						
RLGS1	.994**	.990**	1.000					
RLPLCA1	.620**	.613**	.639**	1.000				
OPOFR1	.662**	.649**	.676**	.864**	1.000			
OPPL1	.676**	.657**	.683**	.801**	.837**	1.000		
OPDMA1	.583**	.564**	.596**	.833**	.846**	.878**	1.000	
OPLTA1	.620**	.602**	.633**	.823**	.855**	.832**	.861**	1.000

**. Correlation is significant at the 0.01 level (2-tailed).

Appendix 7: Inter-Item Correlation Matrix between Latent Constructs of Reverse Logistics and Competitive Advantage

	RLOS1	RLCE1	RLGS1	RLPLCA1	CACL1	CAMS1	CABR1	CARI1
RLOS1	1.000							
RLCE1	.991**	1.000						
RLGS1	.994**	.990**	1.000					
RLPLCA1	.620**	.613**	.639**	1.000				
CACL1	.654**	.641**	.666**	.933**	1.000			
CAMS1	.669**	.655**	.683**	.865**	.903**	1.000		
CABR1	.648**	.624**	.655**	.820**	.842**	.877**	1.000	
CARI1	.654**	.644**	.667**	.951**	.994**	.907**	.845**	1.000

**. Correlation is significant at the 0.01 level (2-tailed).

Appendix 8: Inter-Item Correlation Matrix between Latent Constructs of Process Innovation and Operational Performance

	PIIS1	PIPRD1	PIPRE1	PIBVA1	OPOFR1	OPPL1	OPDMA1	OPLTA1
PIIS1	1.000							
PIPRD1	.989**	1.000						
PIPRE1	.453**	.454**	1.000					
PIBVA1	.968**	.963**	.448**	1.000				
OPOFR1	.659**	.662**	.694**	.654**	1.000			
OPPL1	.658**	.668**	.744**	.662**	.837**	1.000		
OPDMA1	.569**	.573**	.782**	.564**	.846**	.878**	1.000	
OPLTA1	.611**	.611**	.752**	.608**	.855**	.832**	.861**	1.000

**. Correlation is significant at the 0.01 level (2-tailed).

Appendix 9: Inter-Item Correlation Matrix between Latent Constructs of Process Innovation and Competitive Advantage

	PIIS1	PIPRD1	PIPRE1	PIBVA1	CACL1	CAMS1	CABR1	CARI1
PIIS1	1.000							
PIPRD1	.989**	1.000						
PIPRE1	.453**	.454**	1.000					
PIBVA1	.968**	.963**	.448**	1.000				
CACL1	.647**	.654**	.715**	.643**	1.000			
CAMS1	.668**	.663**	.692**	.662**	.903**	1.000		
CABR1	.638**	.637**	.779**	.636**	.842**	.877**	1.000	
CARI1	.649**	.654**	.723**	.644**	.994**	.907**	.845**	1.000

**. Correlation is significant at the 0.01 level (2-tailed).

Appendix 10: Inter-Item Correlation Matrix between Latent Constructs of Operational Performance and Competitive Advantage

	OPOFR1	OPPL1	OPDMA1	OPLTA1	CACL1	CAMS1	CABR1	CARI1
OPOFR1	1.000							
OPPL1	.837**	1.000						
OPDMA1	.846**	.878**	1.000					
OPLTA1	.855**	.832**	.861**	1.000				
CACL1	.881**	.793**	.818**	.867**	1.000			
CAMS1	.903**	.832**	.827**	.922**	.903**	1.000		
CABR1	.840**	.871**	.899**	.927**	.842**	.877**	1.000	
CARI1	.886**	.807**	.830**	.869**	.994**	.907**	.845**	1.000

**. Correlation is significant at the 0.01 level (2-tailed).

Appendix 11: Letter for Data Collection

UNIVERSITY OF NAIROBI
COLLEGE OF HUMANITIES & SOCIAL SCIENCES
SCHOOL OF BUSINESS

Telephone: 4184160-5 Ext 215
Telegrams: "Varsity" Nairobi
Telex: 22095 Varsity

P.O. Box 30197
Nairobi, KENYA

22nd August, 2018

TO WHOM IT MAY CONCERN

Dear Sir/Madam,

INTRODUCTORY LETTER FOR RESEARCH
MWANYOTA JOB LEWELA – REGISTRATION NO. D80/60629/2010

The above named is a registered PhD student at the University of Nairobi, School of Business. He is conducting research on ***"Reverse Logistics, Process Innovation, Operational Performance and Competitive Advantage of Manufacturing Firms in Kenya".***

The purpose of this letter is to kindly request you to assist and facilitate the student with necessary data which forms an integral part of the research project. The information and data required is needed for academic purposes only and will be treated in **Strict-Confidence**.

Your co-operation will be highly appreciated.

Thank you.

Graduate Studies Office
P.O. Box 30197
NAIROBI

Prof. Mary Kinoti
Associate Dean, Graduate Business Studies
School Of Business

MK/nm