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Leveraging Ai to Enhance Reverse Logistics, Returns, Satisfaction and Outcome

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ABSTRACT

This study examines the role of reverse logistics within the industrial sector of Coimbatore, focusing on optimizing return management, enhancing customer satisfaction, and promoting sustainable business practices. By pinpointing local challenges and potential strategic enhancements, this research offers practical insights into how reverse logistics can enhance customer loyalty and yield environmental advantages in this specific industrial setting. A descriptive study with a sample size of 269 is conducted in Coimbatore's e-commerce industry across food and beverages, apparel, electronics, and engineering sectors. Targeting logistics personnel, the study explores and focuses on five main variables: environment, return management, customer satisfaction, and performance effectiveness. Through statistical analysis, this research aims to identify significant factors impacting reverse logistics in these categories, offering insights into optimizing practices for improved customer and operational outcomes. The study highlights actionable measures that can improve operational performance and elevate customer satisfaction, all while cutting costs and promoting sustainability.

Keywords: Reverse logistics, Return Management, Customer Satisfaction, Business environment, Coimbatore industry, Sustainability, Logistics personnel

INTRODUCTION

The swift evolution of global markets has heightened the need for effective logistics systems, making reverse logistics a pivotal focus for companies (Sharma, 2022). Reverse logistics involves managing the return of items from consumers back to suppliers, serving not only as a means to streamline operations but also as a strategy for enhancing customer satisfaction, increasing profitability, and advancing sustainability efforts (Patel & Gupta, 2021). In Coimbatore, a region celebrated for its robust textile, engineering, and manufacturing industries, the proper execution of reverse logistics is especially pertinent (Kumar & Verma, 2020). This study analyzes the adoption of reverse logistics in various industries within Coimbatore, detailing its effects on return management, customer satisfaction, and environmental sustainability (Balakrishnan & Thomas, 2020). Furthermore, we examine how artificial intelligence (AI) can optimize reverse logistics processes, ensuring a data-informed, efficient, and customer-focused approach (Singh & Choudhary, 2023).

Meaning of Reverse Logistics

Reverse logistics refers to the backward movement of goods within the supply chain, originating from the consumer's point and heading back to the source or specific facilities. This process encompasses a range of activities, including returns, inspections, refurbishing, reselling, recycling, and the disposal of products (Nair & Rao, 2019). Unlike traditional logistics, which mainly deals with the forward flow of goods to customers, reverse logistics aims to recover value, handle returns, and minimize waste (Ahmed & Kumar, 2019). Its significance has become more pronounced in sectors that regularly deal with product returns, particularly as companies strive to adhere to environmental standards and satisfy customer expectations for hassle-free returns (Rajan & Iyer, 2021).

Reverse Logistics with AI

Artificial intelligence (AI) is transforming reverse logistics by providing advanced tools for forecasting return patterns, optimizing operations, and enhancing decision-making processes (Das & Bhattacharya, 2023). AI-based solutions—like machine learning, predictive analytics, and natural language processing—help businesses examine consumer behavior, project return volumes, and improve resource allocation (Mehta, 2022). For example, AI-enhanced chatbots improve customer service by offering immediate help with return-related inquiries, while machine learning techniques can pinpoint products that may pose challenges or anticipate the demand for refurbished items (Singh & Choudhary, 2023). By incorporating AI into reverse logistics, companies can increase precision, reduce processing durations, and improve the overall customer experience (Nair & Rao, 2019).

Functions of AI-Driven Reverse Logistics

AI-driven reverse logistics offers a range of features, such as demand forecasting and inventory oversight, enabling businesses to predict return trends and guarantee that adequate resources are allocated effective reverse logistics management (Srinivasan & Kumar, 2022). Automated assessment and quality assurance harness AI-powered image recognition and automated inspection technologies to quickly assess product conditions, enhancing both speed and accuracy of return processing (Choudhary & Iyer, 2021). Improved customer support capabilities arise from AI-based chatbots and virtual assistants that deliver instant assistance, helping customers through the return procedure and reducing response delays (Nair & Pillai, 2021). Cost efficiency, backed by predictive analytics, allows companies to cut down on unnecessary shipping expenses, optimize routes, and allocate resources to areas that greatly influence operational efficiency (Desai, 2020). Additionally, AI-enabled sustainability monitoring allows organizations to track and report on sustainability indicators, ensuring compliance with environmental laws while supporting corporate social responsibility efforts (Ahmed, 2022).

Growth of Logistics in India

Over the last ten years, India's logistics industry has seen significant expansion, fueled by economic progress, increased consumption, and the growth of e-commerce (Raj & Sharma, 2019). The focus on reverse logistics has intensified as companies acknowledge the importance of managing returns efficiently and sustainably (Khan & Reddy, 2023). The Indian government's dedication to sustainable practices, along with the integration of advanced technologies, has encouraged industries to build effective reverse logistics systems (Saxena & Menon, 2020). Various sectors are adopting artificial intelligence solutions to enhance supply chain operations, positioning India as an active market for logistics technology innovation (Bhardwaj, 2021). Consequently, reverse logistics has become a vital component of modern supply chains, improving operational effectiveness, promoting sustainability, and increasing customer satisfaction (Sharma & Das, 2023). By implementing AI, businesses in Coimbatore's industrial sector can markedly refine their reverse logistics strategies, aligning with international standards and contributing to the growing logistics environment in India (Krishnan & Nair, 2022).

REVIEW OF LITERATURE

Thu H.T.T et al., (2024), reverse logistics including product recovery and return tasks have influenced customer happiness in e-commerce. Also, proper return procedures, affordable prices, and first-rate customer support can immensely improve consumer satisfaction by this study. In Vietnamese environment of the rapid growth of the e-commerce, reverse logistics is vital for competitiveness and customer loyalty for cost, return time as well as for regulatory clarity.

Batrisyia N.A & Fernando Y (2024) reverse logistics can enhance the product return processes efficacy. Two big problems that firms deal with and that stop the best possible handling return handling is poor trash management and ineffective communication. The findings could help put a strong circular reverse logistics system into place that would increase customers' happiness, reduce costs and foster sustainability. Some tactics include product labelling and packaging enhancement, expediting return procedures and encouraging cooperation among stakeholders.

Ferraro. S (2023) The research demonstrates that in the field of Logistics 4.0, sustainable Logistics is that it priorities the mutual compatibility (harmony) of social, environmental and economic sustainability. This study proves how Industry 4.0 technologies like robotics, IoT, AI, big data analytics etc, have help in reducing waste and increase operational efficiency of the logistics operations. They point out research gaps in evaluating the effects of these technologies on multiple sustainability dimensions.

Hwang. S. O *et al.*, (2023), an ideal reverse logistics plan is important to make retail operations most profitable and sustainable as possible. To adjust their reverse logistics network, the businesses should have a sophisticated understanding of the rate at which the products they produce depreciate in value. There are cost effective logistics on low value items and responsive return on high value products.

Puranik A (2023) in this study, crowd-sourced testing yields scalability, wide device coverage, and testing in real world environments via a widely distributed community of independent test engineers. The upside of in-house testing is it offers more control, domain knowledge, and faster feedback loops, all of which can be important in some circumstances. But the down side of trying to manage remote engineers under these circumstances, while also protecting data privacy and sustaining efficient communication can be difficult.

Rodriguez-Garcia. M *et al.*, (2023) The study compared warehouse based and retail store-based operations. It applies a framework of Time-driven Activity Based Costing (TDABC) to evaluate the impact of each method on cost drivers for a wide range of activities, including picking, delivery and storage. The retail store model is more expensive than the model where there is picking and other labour-intensive operations. Two lesser-known cost constituents that combine to account for about one third of total expense in both models are unpacking and reverse logistics.

Monnagaaratwe K. F & Mathu K (2022) has reported six main issues emerged from the study: competitive advantage, supplier relationships, rivalry management, customer service, advantages of SCM, supply chain difficulties. Analysis revealed that supplier customer cooperation can be highly efficient and primarily leads to increased operational effectiveness by optimizing certain third-party logistics (3PL) shipping costs during the pandemic of COVID-19.

Ahsan.M.J *et al.*, (2022) surveyed 170 top managers from Pakistan's manufacturing industries and learnt about the impact of lean and green techniques as well as reverse logistics. The results from the study indicate that green practices promote a positive impact on organizational performance and that these green practices are heightened by reverse logistics and lean methods. The way reverse logistics works as mediators, improves the impact of green initiative performance. Reverse logistics leads to recycling and reuse, thinning methods decrease waste and green practices have a beneficial effect on environment and operations.

Wijewickrama, M. K. C. S *et al.*, (2022) The study employs the Organisational Information Processing Theory (OIPT) to analyse quality assurance (QA) in reverse logistics supply chains (RLSCs) in order to improve management of demolition debris (DW). To achieve high-quality recycled materials, the study identifies information processing and input requirements that are necessary to guarantee high quality and highlights the uncertainties that influence quality assurance (QA) in terms of demand and supply chain.

Mishra S. & Singh S. P. (2022) This research focuses on enhancing post-sale services within a global production and distribution network, specifically regarding warranty returns. The proposed model introduces hybrid structures that function both as storage and repair/remanufacturing sites, effectively merging forward and reverse logistics. Rather than constructing new facilities, the model explores possibilities for expanding existing ones, which boosts operational versatility and minimizes disruptions in the supply chain and demand.

Trevisan, A. H. *et al.*, (2021) This study focuses on the roles and duties of stakeholders in the reverse logistics process in Product Service Systems (PSS) for a circular economy in the healthcare industry of Brazilian medical device businesses. These studies embody the experience of how resource recovery and reuse can be coordinated with reverse logistics which are key enablers of PSS and the circular economy and support for reverse logistics. These studies in detail cover relevance of a cooperative approach for maintenance, collection, and disposal phases.

Attia. A (2021) The study analyses how the information system components (capability, compatibility and technology) might contribute to cost effectiveness and efficiency of the reverse logistics system with the use of 165 Saudi food sector data. Results suggest that components of the information system are positively related to management and operational efficacy. More capable information systems provide improved timely and accurate data, which affects improved decision making, and lower processing costs.

Foo.Y.J. *et al.*, (2021) study major concepts that enhance the quality of reverse logistics management. To boost user happiness, and for organisations that have taken the forward-thinking step of introducing features like in store returns, Customer centric return policies should be a priority. Also, eco-friendly are highlighted in alignment with the desire of the customers for a sustainable return handling process and legal compliance. Reverse logistics systems in omnichannel market are very efficient and can give competitive edge because they retain customers.

Yu. In H *et al.*, (2020) the study identifies and introduces a new multi objective model that aims to maximize placement and functionality of temporary facilities to cope with medical waste spikes. With the purpose of reducing health hazard both to general public and medical staff, the suggested model combines the cost effectiveness, quick response, and risk reduction. A case study demonstrates how a logistical network that temporarily combines hazardous waste produced during the outbreak and stores it at key places can help manage the vast quantities of hazardous material created during the outbreak.

Phuong N.H. *et al.*, (2019) highlight the importance of reverse logistics in modern supply chain practice. Efficient reverse logistics helps to boost income, reduce expenses, and enhance customer happiness while at the same time promoting the environmental sustainability. This study explores the use of third-party logistics (3PL) providers to carry out recovery operations using various reverse logistics model such as closed loop and open loop systems. These advantages are large service networks, cost reductions, high levels of competence and continued logistical activity optimization.

Muha. R (2019) This study's comprehensive exploration of logistics cost management problems has highlighted the impact of logistics on the overall company costs and profitability. The benefit of improving logistics service may come with increased cost. Because the cost components like transportation, warehousing and inventory are mutually dependent. This study addresses delivering logistics cost and discusses the current practices realizing the shortcomings of same in particular in the imbalance cost of logistics. According to the study reported, businesses should leverage strong measurement and modeling tools to improve logistical decision making as they balance logistics costs and customer satisfaction strategically.

Kinyanjui Njuguna E & Kagiri D.A (2017) found that reverse logistics methods, such as product returns, reuse, and repackaging, significantly influence the operational performance of Bata Shoe Company in Kenya. These techniques enhance operational efficiency, decrease costs, and improve customer satisfaction. While product returns can impact communication between departments, influence procurement decisions, and affect inventory management, they may also lead to increased operational costs.

Milichovsky. F (2016) While the study focuses on the attitudes of 585 people polled, the reported an important number of the end consumers produces municipal garbage rather than recycling or reusing, emphasising the need for effective techniques of communication to support RL activities. The study shows that businesses need to incorporate reverse logistics services into their products, in order to satisfy increased customer interest in sustainability.

Mehidi S.H. *et al.*, (2014) conducted a study focused on in-house recycling methods in Bangladesh, specifically examining reverse logistics within the steel industry. They developed a transportation model aimed at reducing CO2 emissions and the costs associated with transporting internal scrap. Utilizing linear optimization (TORA), the research assesses a proposed single-site scrap collection model in comparison to an existing two-site model. The findings indicate that the proposed model enhances environmental performance, leading to a 7% reduction in CO2 emissions and a 19% decrease in transportation costs.

Jeszka A. M (2014) investigates the effectiveness of returns management in the supply chains of Polish retail clothing stores. Effective returns management enhances customer relationships, reduces expenses, and aids in controlling inventory and recovering value. Retail chains often manage tasks like product inspection, sorting, and resale internally, while logistics activities, including transportation and product retrieval, are typically outsourced to external service providers.

Oko. A.E.N *et al.*, (2013) This study investigates the difficulties and effects of reverse logistics management in Nigeria's food and the beverage sectors. The main topics of study are limitations on the use of garbage recycling and reuse, as a result of lack of policies, cultural norms and technological restrictions. The difficulties are solved and it is suggested that reverse logistics might help enhance environmental outcomes, as well as contribute to corporate social responsibility.

Bogataj. M & Grubbstrom. R.W (2013) The study, needed the integration of reverse logistics and Material Requirements Planning (MRP) theory to develop efficient transportation delay management. Four sub-systems within the supply chain are observed by the model that combines input-output analysis and Laplace transforms: It includes manufacturing, distribution, consumption, reverse logistics. The model assesses the impact of physical distances and types of transportation on economic performance, in particular, the Net Present Value (NPV).

Dat L.Q *et al.*, (2012) conducted a comprehensive analysis of the reverse logistics network for waste electrical and electronic products (WEEPs), emphasizing the importance of effective management due to their complex and hazardous nature. The study introduces a mathematical programming approach aimed at minimizing the overall processing costs associated with different types of WEEPs This model considers various financial factors, including potential revenue from returned items, as well as costs linked to collection, treatment, and transportation.

Wang. D.S & Koo. T. Y (2010), used their study on a plastic recycling facility in Taiwan to focus on reverse logistics. This has an inventory approach where reverse and forward logistics are combined. As a case study, this report demonstrates how such a step reduces safety stock by 41.19%, reorder quantity by 50.96% and incurs 12.82% lower inventory expenses, and hence helps businesses save money and further reduce environmental impact by increasing recycling rates while integrating reverse logistics into the larger supply chain.

Oom Do Valle. P *et al.*, (2009), The factors encouraging and impeding teleworking in the United Arab Emirates fill a gap in the body of literature written on developed nations. Results indicate that demographic characteristics matter for teleworking decisions. But the report also highlights important benefits that employees who choose teleworking enjoy more, such as cost savings, travel, and freedom. Employees' choices of teleworking may not make much difference to how much importance they give to teleworking inhibitors. In particular, the study provides useful implications for firms interested in varying teleworking rules, and calls for more research in more developing situations.

Motte. D *et al.*, (2007) the study describes the four integration strategies in the totality of integration, expanded enterprise, virtual enterprise, and supplier buyer relations and differs in the levels of co-operation and the use of resources by packaging and product development teams. Study early package development findings do reduce out-of-pocket expenses, minimize delays, and improve product quality. Using these tactics, businesses are better able to synchronize packaging with product requirements, with improved results for operations.

Chouinard M.D. *et al.* (2005) noted in their study that managing unwanted, returned, or end-of-life products is a strategy to boost resource efficiency and promote sustainability. The research demonstrates how reverse logistics methods, such as recycling, refurbishment, and remanufacturing, can be effectively integrated into existing supply chains, particularly within the healthcare sector in Quebec. To enhance the coordination of labor, materials, and technology, a new information framework and organizational model were proposed. The study concludes that reducing waste, optimizing resource use, and establishing a sustainable closed-loop system for managing product lifecycles are crucial goals.

Krikke. H. R *et al.*, (1999) The study focuses on improving logistics flow and facility location. The model looks at issues with handling return flows in supply chains by identifying the best places for processing facilities such as shredders and disassembly stations. Finally, using a mixed-integer linear programming (MILP) technique, the study proposes an organized way to reduce transportation, processing and facility investment costs. The results show that reverse logistics network can be maximized by judiciously balancing flow management, investment costs and facility locations.

Research Design

Statement of the problem

In the context of reverse logistics within the Food and Beverages (F&B), Apparel (A), Electronics (E), and Engineering (Eng) sectors and e-commerce industry in Coimbatore, particularly focusing on this study aims to explore the key factors influencing the effectiveness of reverse logistics processes, customer satisfaction, and overall business performance. Specifically, the problem revolves around understanding the complex relationships between return management, environmental sustainability, customer satisfaction, and performance effectiveness in reverse logistics. The study will employ Structural Equation Modeling (SEM) to identify latent variables and their relationships, regression analysis to examine the impact of various factors on customer satisfaction and operational performance, descriptive statistics to summarize data and provide an overview of reverse logistics practices, and factor analysis to reduce dimensionality and identify underlying factors that contribute to the success of reverse logistics systems.

Objectives

- To identify and evaluate key variables (e.g., return management, environmental practices, customer service) influencing the success of reverse logistics in e-commerce, with a focus on sectors in Coimbatore.
- To analyze the impact of reverse logistics practices on customer satisfaction (CS) and performance effectiveness (PE) through regression modeling.
- To determine the interrelationships between different factors influencing reverse logistics processes using SEM.
- To apply descriptive statistics to quantify the prevalence of various reverse logistics practices and challenges across sectors.
- To perform factor analysis to extract the key dimensions that most significantly affect reverse logistics and suggest strategies for improvement.

Research Design

The setting of this descriptive study is to look at the phenomenon of reverse logistics in the e commerce industry in Coimbatore with food and beverage, apparel, electronics and engineering sectors incorporating 269 participants. To investigate critical aspects in reverse logistics processes in environment, return management, customer satisfaction, and performance effectiveness the study focused on logistics workers. The study uses statistical analysis to identify major factors impacting the conducting of reverse logistics in different industries to give ideas on how to enhance processes in order to improve the level of customer service and efficiency of operation.

Hypothesis framework

H1: Effective Return Management (RM) has a positive significant impact on Customer Satisfaction (CS) in reverse logistics.

H2: The adoption of Environmental Practices (EP) in reverse logistics positively affects Performance Effectiveness (PE).

H3: Integration of Reverse Logistics (IRL) into the overall supply chain significantly enhances Operational Performance (OP).

H4: Customer Satisfaction (CS) positively influences Business Performance (BP) in reverse logistics.

H5: Return Management (RM) and Environmental Practices (EP) collectively have a significant positive effect on Performance Effectiveness (PE) in reverse logistics.

H6: Factor Analysis (FA) will identify key underlying factors that influence the success of reverse logistics in e-commerce.

H7: Return Time (RT) has a significant positive effect on Customer Satisfaction (CS).

H8: Packaging Strategy (PS) significantly impacts the efficiency of Return Management (RM) in reverse logistics.

H9: Legal and Regulatory Compliance (LRC) moderates the relationship between Return Management (RM) and Customer Satisfaction (CS).

Statistical tools used for the study

The study will utilize several statistical tools to analyze the data and test the hypotheses. Descriptive statistics will be used to summarize the dataset and provide an overview of reverse logistics practices, customer satisfaction, and performance effectiveness. Regression analysis (multiple and linear) will examine the impact of factors like return management and environmental practices on customer satisfaction and operational performance. Structural Equation Modeling (SEM) will help test the hypothesized relationships between latent and observed variables, exploring the direct and indirect effects on business performance. Factor analysis (both exploratory and confirmatory) will identify underlying factors influencing reverse logistics practices. Cronbach's alpha will measure the reliability of scales used to assess key constructs, and path analysis within SEM will analyze the causal relationships and strength between the variables. These tools together will provide a robust analysis of the data, offering insights into the effectiveness of reverse logistics in the e-commerce industry.

Model framework & variables for the study

Reverse Logistics (RL)

Effective reverse logistics begins with a comprehensive Planning System Evaluation (RL1), ensuring that the infrastructure in place can adapt to the complexities of returns management. Key insights are derived from Return Insights (RL2), which use data analysis to detect patterns in return rates and reasons, supporting proactive improvements. For sustainability and cost efficiency, Material Breakdown (RL3) classifies returned items for reuse, recycling, or disposal based on their condition and market value. Quality Assurance (RL4) plays a crucial role in upholding standards for items earmarked for resale or refurbishment, ensuring customer satisfaction and brand reputation. Transport Selection (RL5) is carefully managed to optimize routes and modes for cost-effective and timely returns. Integrating reverse logistics effectively across the entire supply chain, Integration of Reverse Logistics (RL6) ensures seamless operations and supports resource optimization. Lastly, Inventory Oversight (RL7) involves constant monitoring of return stocks, helping minimize holding costs and preventing warehouse congestion, which is essential in sectors like Food and Beverage (F&B) and Electronics where demand and turnover rates are high.

Environment (EN)

Environmental sustainability is increasingly prioritized in reverse logistics, starting with Third-Party Collaboration (EN1), where partnerships with eco-friendly vendors enhance green practices across the supply chain. Leveraging In-House Expertise (EN2) allows companies to design and implement sustainability measures that fit their unique operations, especially in Coimbatore's diverse industries. Core Environmental Practices (EN3)—such as recycling and waste reduction—are integrated throughout reverse logistics processes, aligning with global standards. Supporting these initiatives is Technical Support Definition (EN4), which outlines the scope of technical expertise and resources required to maintain sustainability goals, especially in engineering and electronics sectors. In Transport Decision (EN5), companies choose sustainable options like fuel-efficient vehicles and optimized route planning, minimizing the environmental impact of returns. Finally, Lean Practices (EN6) are employed to reduce waste and improve overall efficiency, supporting a circular economy model that reflects customer expectations for environmental responsibility.

Return Management (RM)

Return management is streamlined through a structured Return Authorization (RM1) process that simplifies approval for returns, reducing delays and boosting customer confidence. Product Inspection and Sorting (RM2) is crucial to ensure that returned items are evaluated accurately for quality and usability, categorizing them for potential Repair, Refurbishment, and Remanufacturing (RM3). This phase not only adds value to returned items but also minimizes waste. For products suitable for resale, Repackaging and Restocking (RM4) ensures they are reintegrated into inventory efficiently, ready for distribution. Items that cannot be reused are handled through Disposal or Recycling (RM5), supporting eco-friendly waste management. Ensuring compliance with Legal and Regulatory Compliance (RM6) requirements further solidifies the process, as companies adhere to local and global standards, avoiding legal issues and maintaining accountability in sectors like apparel and engineering.

Customer Satisfaction (CS)

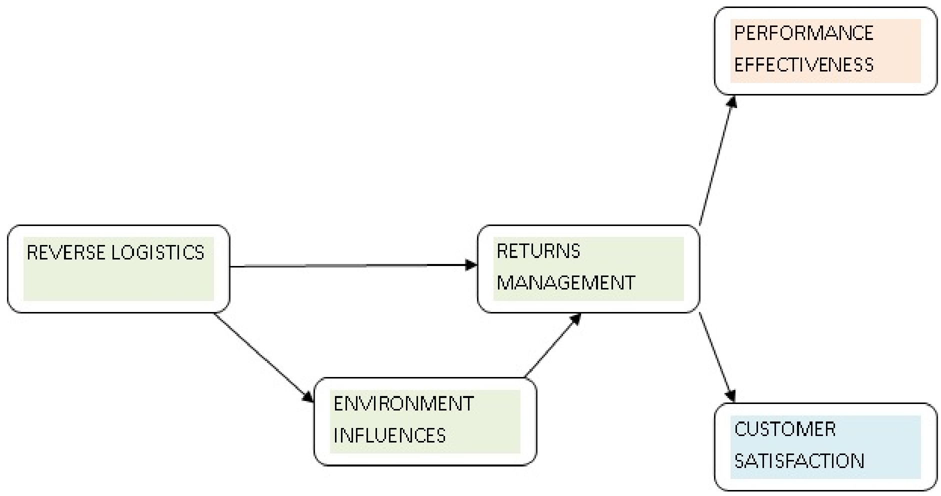
Customer satisfaction in reverse logistics hinges on delivering seamless service, with Outsourcing Satisfaction (CS1) ensuring that third-party providers meet high standards in handling returns. Addressing customer Issues & Stakeholder Identification (CS2) proactively helps resolve concerns swiftly, maintaining trust. Information Handling (CS3) facilitates transparent communication with customers, providing real-time return tracking and status updates. Efficient Activity Scheduling (CS4) minimizes waiting periods, enhancing the customer experience, particularly in sectors where time-sensitive returns are essential, such as electronics. Expense Management (CS5) ensures that return-related costs are controlled without compromising quality, and Return Time Value (CS6) quantifies the added value of swift processing. The cornerstone of this category is Customer Service and Communication (CS7), where responsive and personalized support reassures customers, encouraging loyalty and retention.

Performance Effectiveness (RE)

Performance effectiveness in reverse logistics encompasses strategic planning in areas like Packaging Strategy (RE1), where durable and sustainable packaging solutions reduce damage during returns. Warehousing Strategy (RE2) plays a pivotal role in efficiently managing the storage and processing of returned items, optimizing space and reducing handling times. A well-defined Operational Strategy (RE3) ensures that the reverse logistics system operates smoothly, meeting key performance goals. Location Selection (RE4) for processing facilities is strategically managed to minimize costs and improve speed, especially critical for sectors with high return rates. Cost Management (RE5) is crucial to keeping reverse logistics financially viable, balancing expenses across various stages. Logistics Network Design (RE6) builds an optimized infrastructure for efficient returns handling, while Risk Management (RE7) mitigates potential disruptions, helping companies maintain high levels of service and reliability across the reverse logistics chain.

Theoretical Model

Figure 1. Proposed Model for AI Integrated Reverse Logistics



Analysis & Interpretation

Descriptive Statistics

Table 1. Showing descriptive statistics of the respondents

Descriptive statistics	Gender	Age	Experience	Industry	Role	Familiarity of AI
Mean	1.3234	2.4201	2.5242	2.7918	2.7732	3.0818
Std. Deviation	.46865	1.41095	1.32301	1.53849	1.40517	1.15932
Variance	.220	1.991	1.750	2.367	1.975	1.344
Skewness	.759	.542	.469	.131	.247	-.305
Std. Error of Skewness	.149	.149	.149	.149	.149	.149
Kurtosis	-1.434	-1.070	-.931	-1.491	-1.233	-.844
Std. Error of Kurtosis	.296	.296	.296	.296	.296	.296

The dataset shows a moderate spread across categories, with the mean values indicating averages close to 1.32 for Gender, 2.42 for Age, 2.52 for Experience, 2.79 for Industry, 2.77 for Role, and 3.08 for Familiarity with AI. Standard deviations reveal variation across these categories, particularly high in Industry (1.54) and Role (1.41). Skewness values are positive for most variables, with Gender at 0.759 and Age at 0.542, suggesting a slight tilt toward certain categories, while Familiarity with AI shows a minor negative skew (-0.305), indicating a slight tendency toward higher familiarity levels. Kurtosis values are all negative, such as -1.434 for Gender and -1.491 for Industry, suggesting flatter distributions with responses spread relatively evenly rather than tightly clustered around the means. This combination of values highlights a diverse range of responses, particularly in industry and role

Simple Percentage Analysis: Distribution of Reverse Logistics Practices and Customer Satisfaction

Table 2: Demographic statistics of the respondents (N=269)

Category	Frequency	Percentage
Gender		
Male	182	67.7
Female	87	32.3
Age		
18 Years - 25 Years	101	37.5
26 Years - 35 Years	56	20.8
35 Years - 45 Years	41	15.2
46 Years - 55 Years	40	14.9
55 Years above	31	11.5
Experience		
Less than 5 Years	76	28.3
6 Years - 10 Years	72	26.8
11 Years - 15 Years	54	20.1
16 Years - 20 Years	38	14.1
More than 20 Years	29	10.8
Industry		
E Commerce	88	32.7
Food and Beverages	35	13.0
Apparel	43	16.0
Electronic Products	51	19.0
Engineering	52	19.3
Role		
Transportation	64	23.8
Operation and Warehourse	66	24.5
Customer Service	50	18.6
Data Management	45	16.7
Repairs Maintenance	44	16.4

Familiarity of AI		
In basic awareness level	32	11.9
Data Entry level	52	19.3
Operational level	69	25.7
Optimise process level	94	34.9
Strategic decision level	22	8.2

In a sample of 269 respondents, the Gender distribution shows 67.7% male and 32.3% female participants. Age categories reveal that 37.5% are aged 18-25, followed by 20.8% in the 26-35 range, with smaller percentages in older groups (15.2% aged 35-45, 14.9% aged 46-55, and 11.5% above 55 years). Regarding Experience, 28.3% have less than 5 years, 26.8% have 6-10 years, and progressively fewer have longer experience, with only 10.8% having over 20 years. For Industry, E-Commerce leads at 32.7%, followed by Electronics (19.0%), Engineering (19.3%), Apparel (16.0%), and Food and Beverages (13.0%). In Roles, Operations and Warehouse roles are the most common at 24.5%, followed closely by Transportation (23.8%), with fewer in Customer Service (18.6%), Data Management (16.7%), and Repairs/Maintenance (16.4%). Lastly, Familiarity with AI shows a concentration at the Optimized Process level (34.9%), followed by Operational level (25.7%) and Data Entry level (19.3%), with fewer at the Basic Awareness (11.9%) and Strategic Decision levels (8.2%).

Factor Analysis: Identifying Key Dimensions in Reverse Logistics Practices

The extraction method used was Maximum Likelihood.

The ***Kaiser-Meyer-Olkin (KMO)*** measure of sampling adequacy for the dataset is .852, indicating that the data is suitable for factor analysis. A KMO value closer to 1 suggests that the variables share common factors, making factor analysis appropriate. In this case, a value of .852 is considered "meritorious," signifying strong adequacy.

Additionally, ***Bartlett's Test of Sphericity*** produced an approximate chi-square value of 4149.210 with 528 degrees of freedom and a significance level of .000. This highly significant result indicates that the null hypothesis, which assumes that the correlation matrix is an identity matrix (i.e., variables are unrelated), can be rejected. The significant p-value confirms that there are enough correlations between variables to justify the use of factor analysis.

In the analysis, the first five factors collectively explain a significant portion of the total variance. Initially, these factors account for 51.453% of the variance, with each subsequent factor contributing less. The first factor alone explains 14.414% of the variance, the second 11.387%, the third 9.664%, the fourth 8.612%, and the fifth 7.377%. This cumulative explanation reflects a substantial portion of the total variance in the dataset, highlighting the primary dimensions or constructs identified through the factor analysis.

Communality

The communality analysis examines how well each item is explained by the factors, with some items showing strong representation in the model and others revealing areas for potential improvement. In reverse logistics, items like Planning System Evaluation (initial: 0.322, extraction: 0.198) and Return Insights (initial: 0.431, extraction: 0.418) exhibit moderate communalities, while Material Breakdown (initial: 0.464, extraction: 0.504), Quality Assurance (initial: 0.441, extraction: 0.461), and Transport Selection (initial: 0.482, extraction: 0.511) have extraction values that indicate they are well-captured by the model. Integration of Reverse Logistics (initial: 0.485, extraction: 0.538) and Inventory Oversight (initial: 0.366, extraction: 0.389) also contribute effectively within this factor.

In reverse logistics environment, Third-Party Collaboration (initial: 0.301, extraction: 0.233) shows a relatively low extraction value, indicating a weaker representation, while items such as In-House Expertise (initial: 0.615, extraction: 0.656) and Environmental Practices (initial: 0.654, extraction: 0.690) are strongly represented. Technical Support Definition (initial: 0.561, extraction: 0.570) and Transport Decision (initial: 0.573, extraction: 0.609) also show high communality values, suggesting that these environmental practices are crucial in capturing reverse logistics variability. For return management, Return Authorization (initial: 0.350, extraction: 0.322) shows moderate representation, while Repair, Refurbishment, and Remanufacturing (initial: 0.556, extraction: 0.592) and Repackaging and Restocking (initial: 0.612, extraction: 0.672) reflect strong communality.

Items in satisfaction, such as Outsourcing Satisfaction (initial: 0.494, extraction: 0.453) and Return Time Value (initial: 0.597, extraction: 0.588), display solid communality values, indicating a good model fit for satisfaction aspects. Issue & Stakeholder Identification (initial: 0.630, extraction: 0.699) shows a particularly strong extraction, highlighting its importance. In performance effectiveness, Operational Strategy (initial: 0.690, extraction: 0.735) and Warehousing Strategy (initial: 0.643, extraction: 0.667) stand out with high communality, whereas Cost Management (initial: 0.497, extraction: 0.400) and Risk Management (initial: 0.444, extraction: 0.362) have lower values, indicating that these items may require additional factors to fully capture their variance. This analysis provides a comprehensive view of how well the model explains each item and where further adjustments might enhance the explanatory power for lower-communalities items.

Regression Analysis: Evaluating the Impact of Reverse Logistics Factors on Customer Satisfaction and Performance

Table 3: Industry significant impacts on AI-Integrated Reverse Logistics

Industry	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.414[a]	.171	.055	1.49556	.171	1.473	33	235	.054
a. Predictors: (Constant), RL1, RL2, RL3, RL4, RL5, RL6, RL7, EN1, EN2, EN3, EN4, EN5, EN6, RM1, RM2, RM3, RM4, RM5, RM6, CS1, CS2, CS3, CS4, CS5, CS6, CS7, RE1, RE2, RE3, RE4, RE5, RE6, RE7									

The Model Summary presents the results of industry a regression analysis with an R value of 0.414, indicating a moderate positive correlation between the predictors and the outcome variable. The R Square value of 0.171 suggests that approximately 17.1% of the variance in the dependent variable is explained by the predictors. The Adjusted R Square value of 0.055 adjusts for the number of predictors, indicating a smaller proportion of explained variance after accounting for model complexity. The Standard Error of the Estimate is 1.49556, which represents the average distance between the observed and predicted values. The Change Statistics show an R Square Change of 0.171, and an F Change value of 1.473 with degrees of freedom (df1 = 33, df2 = 235), with a Sig. F Change of 0.054, which is marginally significant at the 0.05 level, indicating that the addition of predictors provides a small but notable improvement to the model’s explanatory power.

In this regression analysis, the constant has a significant positive effect (B = 2.123, p = 0.001). Key predictors with significant or near-significant effects on Industry include Lean Practices (B = -0.208, p = 0.029), indicating a negative relationship, and Information Handling (B = 0.269, p = 0.011) and Location Selection (B = 0.240, p = 0.037), both showing positive associations. Activity Scheduling (B = -0.212, p = 0.040) and Issue & Stakeholder Identification (B = -0.180, p = 0.103) indicate a negative impact on Industry. Risk Management (B = 0.207, p = 0.030) and Planning System Evaluation (B = 0.147, p = 0.100) also show positive effects, while Operational Strategy (B = -0.224, p = 0.063) suggests a marginally negative relationship. Other variables like Outsourcing Satisfaction (B = 0.186, p = 0.059) also approach significance, suggesting potential influence.

Overall, while some predictors are significant, most show limited effects, as many confidence intervals cross zero, indicating modest influence on Industry.

Table 4: Experience significant impacts on AI-Integrated Reverse Logistics

Experience	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.495[a]	.245	.139	1.22783	.245	2.308	33	235	.000
a. Predictors: (Constant), RL1, RL2, RL3, RL4, RL5, RL6, RL7, EN1, EN2, EN3, EN4, EN5, EN6, RM1, RM2, RM3, RM4, RM5, RM6, CS1, CS2, CS3, CS4, CS5, CS6, CS7, RE1, RE2, RE3, RE4, RE5, RE6, RE7									

The Model Summary for this experience regression shows an R value of 0.495, indicating a moderate correlation between the predictors and the dependent variable, Industry. The R Square value of 0.245 suggests that 24.5% of the variance in Industry is explained by the predictors. The Adjusted R Square is 0.139, accounting for the model's complexity and still showing a reasonable level of explained variance. The Standard Error of the Estimate is 1.22783, which represents the average deviation of observed values from the predicted values. The Change Statistics indicate an R Square Change of 0.245 with an F Change of 2.308 (df1 = 33, df2 = 235) and a Sig. F Change of 0.000, showing that the predictors significantly improve the model's explanatory power at a high level of confidence.

Considering predictors with p-values up to 0.100 as significant, the regression analysis indicates several noteworthy predictors for Experience. The constant is highly significant (B = 2.275, p = 0.000), setting a strong baseline. Key significant predictors include Integration of Reverse Logistics (B = 0.166, p = 0.045) and Inventory Oversight (B = 0.154, p = 0.030), both showing positive effects on Experience. Lean Practices (B = -0.205, p = 0.009) is a significant negative predictor. Additionally, Information Handling (B = 0.315, p = 0.000) has a strong positive effect, while Return Time Value (B = -0.183, p = 0.041) has a negative impact. Packaging Strategy (B = 0.197, p = 0.030) also significantly influences Experience positively. Predictors with p-values near significance but still within the 0.100 threshold include Technical Support Definition (B = -0.148, p = 0.093), Legal And Regulatory Compliance (B = -0.134, p = 0.086), and Warehousing Strategy (B = -0.179, p = 0.057), which could have subtle influences on Experience.

Table 5: Age significant impacts on AI-Integrated Reverse Logistics

Age	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.518[a]	.268	.165	1.28920	.268	2.606	33	235	.000
a. Predictors: (Constant), RL1, RL2, RL3, RL4, RL5, RL6, RL7, EN1, EN2, EN3, EN4, EN5, EN6, RM1, RM2, RM3, RM4, RM5, RM6, CS1, CS2, CS3, CS4, CS5, CS6, CS7, RE1, RE2, RE3, RE4, RE5, RE6, RE7									

The Model Summary for the regression analysis on Age reveals a moderate correlation between the predictors and the dependent variable, with an R value of 0.518. This suggests a moderate relationship between the variables. The R Square value of 0.268 indicates that 26.8% of the variance in Age is explained by the predictors in the model. The Adjusted R Square of 0.165 takes into account the number of predictors and adjusts for model complexity. The Standard Error of the Estimate is 1.28920, representing the average deviation of the observed values from the predicted values.

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The Change Statistics show an R Square Change of 0.268 and an F Change of 2.606 (df1 = 33, df2 = 235) with a Sig. F Change of 0.000, indicating that the model significantly improves the prediction of Age with high confidence. This suggests that the predictors collectively have a meaningful impact on explaining the variance in Age.

The regression analysis examining the predictors of Age reveals several noteworthy results. The constant is highly significant (B = 2.687, p = 0.000), establishing a strong baseline. Among the predictors, Lean Practices (B = -0.191, p = 0.020) shows a significant negative effect on Age, while Information Handling (B = 0.326, p = 0.000) has a significant positive effect. Warehousing Strategy (B = -0.236, p = 0.017) also significantly influences Age negatively, and Location Selection (B = 0.202, p = 0.041) shows a positive significant effect. Predictors such as In-House Expertise (B = -0.134, p = 0.163) and Issue & Stakeholder Identification (B = -0.150, p = 0.116) approach significance but remain slightly above the 0.100 threshold. Integration Of Reverse Logistics (B = 0.138, p = 0.113) and Return Time Value (B = -0.163, p = 0.081) also show marginal significance.

Table 6: Role significant impacts on AI-Integrated Reverse Logistics

Role	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.461[a]	.213	.102	1.33137	.213	1.925	33	235	.003
a. Predictors: (Constant), RL1, RL2, RL3, RL4, RL5, RL6, RL7, EN1, EN2, EN3, EN4, EN5, EN6, RM1, RM2, RM3, RM4, RM5, RM6, CS1, CS2, CS3, CS4, CS5, CS6, CS7, RE1, RE2, RE3, RE4, RE5, RE6, RE7									

The regression model for predicting Role has an R-value of 0.461, indicating a moderate correlation between the predictors and the dependent variable. The R^2 value of 0.213 means that approximately 21.3% of the variance in Role can be explained by the predictors in the model. The F-change statistic of 1.925 with a significance value of 0.003 indicates that the model as a whole is statistically significant. This means that the combination of predictors contributes to explaining differences in Role.

The regression analysis results for predicting Role show that several predictors significantly influence the dependent variable. The constant term is significant with a value of 2.606, indicating a baseline value for Role. Among the predictors, Material Breakdown (β = 0.180, p = 0.036) is positively significant, meaning it has a positive relationship with Role. Outsourcing Satisfaction (β = 0.260, p = 0.003) also shows a significant positive relationship with Role, suggesting that higher values of Outsourcing Satisfaction contribute to a higher role score. Return Time Value (β = -0.299, p = 0.002) negatively affects Role, indicating that higher values of Return Time Value are associated with a lower role score. Similarly, Warehousing Strategy (β = -0.248, p = 0.015) has a negative effect on Role, and Location Selection (β = 0.373, p = 0.000) has a positive impact. Other variables such as Planning System Evaluation, Return Insights, Transport Selection, Third-Party Collaboration, In-House Expertise, Return Authorization, Product Inspection and Sorting, and Risk Management show no significant effect on Role as their p-values exceed the significance threshold of 0.100.

Table 7: Familiarity with AI significant impacts on AI-Integrated Reverse Logistics

Familiarity with AI	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.493[a]	.243	.137	1.07728	.243	2.284	33	235	.000
a. Predictors: (Constant), RL1, RL2, RL3, RL4, RL5, RL6, RL7, EN1, EN2, EN3, EN4, EN5, EN6, RM1, RM2, RM3, RM4, RM5, RM6, CS1, CS2, CS3, CS4, CS5, CS6, CS7, RE1, RE2, RE3, RE4, RE5, RE6, RE7									

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The regression model for Familiarity with AI indicates that the independent variables explain 24.3% of the variance in the dependent variable, as reflected by an R^2 of 0.243. The F-statistic of 2.284, with a corresponding p-value of 0.000, shows that the overall model is statistically significant, meaning the combination of predictors contributes meaningfully to the prediction of Familiarity with AI.

The adjusted R^2 value of 0.137 suggests that, after adjusting for the number of predictors, about 13.7% of the variability in Familiarity with AI is explained by the model. The standard error of the estimate is 1.07728, indicating the average deviation of the observed data points from the predicted values.

The regression analysis for Familiarity with AI shows that several factors significantly influence the outcome. The constant term is significant ($B = 3.554$, $p < 0.001$), indicating the baseline familiarity with AI. Among the predictors, Repair, Refurbishment, And Remanufacturing ($B = 0.157$, $p = 0.035$), Legal And Regulatory Compliance ($B = -0.148$, $p = 0.030$), and Return Time Value ($B = 0.180$, $p = 0.022$) have a significant impact on familiarity with AI, while other variables like Environmental Practices ($B = 0.153$, $p = 0.068$), Technical Support Definition ($B = -0.154$, $p = 0.047$), and Repackaging And Restocking ($B = -0.149$, $p = 0.054$) show trends approaching significance. Variables such as Planning System Evaluation, Inventory Oversight, Third-Party Collaboration, In-House Expertise, and others do not have significant effects. The overall results indicate that some demographic and operational factors are important predictors of familiarity with AI.

Structural Equation Modelling

Structural Equation Modeling (SEM) is an advanced statistical technique used to analyze complex relationships among multiple variables, both observed and latent. In the context of this study on reverse logistics in the e-commerce industry, SEM provides a robust framework for investigating the interdependencies between key constructs such as return management, environmental sustainability, customer satisfaction, and performance effectiveness. By employing confirmatory factor analysis (CFA) and path analysis, SEM enables the exploration of direct, indirect, and mediated relationships, facilitating a deeper understanding of how various factors influence business outcomes. This analytical approach allows for the validation of theoretical models and the testing of causal pathways, offering a comprehensive and data-driven perspective on reverse logistics processes. SEM is particularly valuable for examining the intricate dynamics within reverse logistics systems, providing both statistical rigor and practical insights for enhancing operational efficiency and customer satisfaction.

Hypothesis

Reverse Logistics Environment has a positive effect on Reverse Logistics.

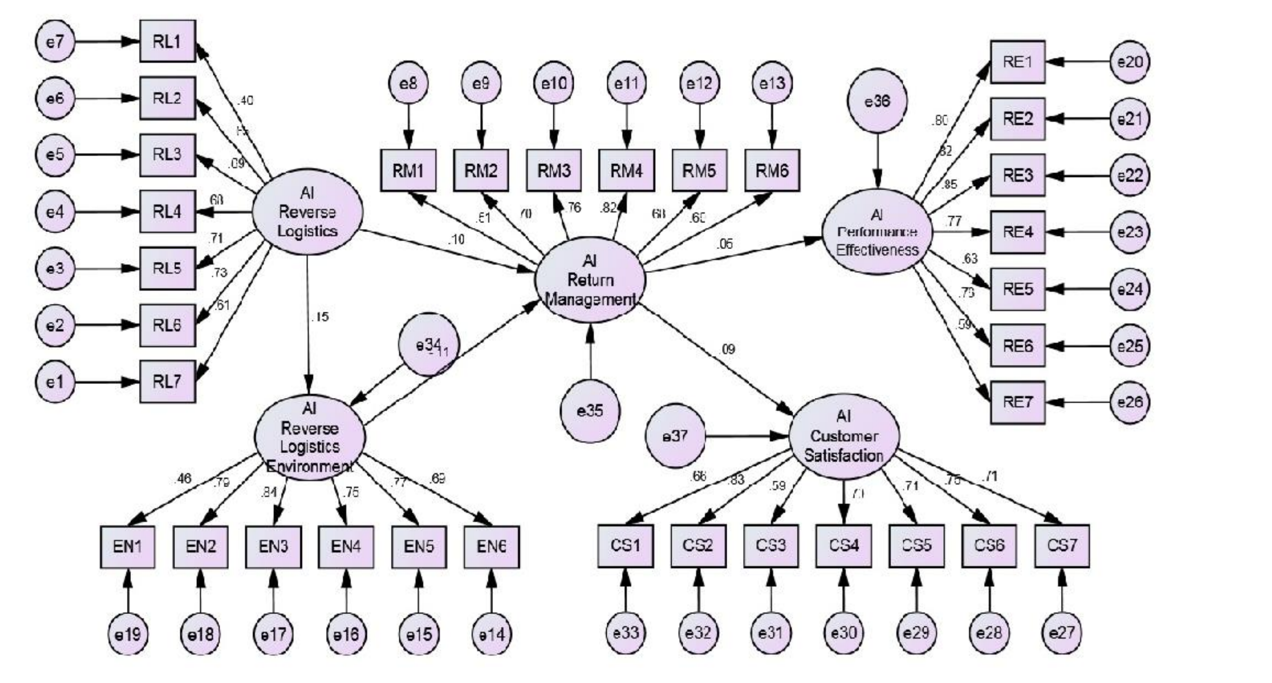
Reverse Logistics has a positive effect on Return Management.

Reverse Logistics Environment has a positive effect on Return Management.

Return Management has a positive effect on Performance Effectiveness.

Return Management has a positive effect on Satisfaction.

Figure 2. Structural Equation Modeling of AI- Integrated Reverse Logistics (AMOS)



The CMIN (Chi-square) values provide insight into the fit of the models. For the default model, with 104 parameters, the chi-square value is 724.765 with 490 degrees of freedom, yielding a significant p-value of 0.000, indicating that the model significantly differs from perfect fit. However, the CMIN/DF ratio of 1.479 is below the threshold of 3, which suggests a good fit. The saturated model (with 594 parameters) has a chi-square of 0.000, reflecting a perfect fit with no degrees of freedom, and therefore no CMIN/DF ratio. The independence model with 66 parameters shows a very high chi-square value of 4340.878 and 528 degrees of freedom, resulting in a CMIN/DF ratio of 8.221, which is well above the acceptable threshold and Overall, the default model demonstrates a good fit according to the CMIN/DF ratio.

The model fit indices indicate that the default model demonstrates a good fit to the data, with the NFI (0.833), RFI (0.820), and CFI (0.938) values suggesting acceptable to good fit, although slightly below ideal thresholds. The IFI (0.939) and TLI (0.934) are both strong, indicating a good model fit, with values above 0.90 typically seen as acceptable. The saturated model, which perfectly fits the data, achieves a value of 1.000 across all indices, while the independence model shows no fit with values of 0.000. Overall, the default model provides a solid fit, though improvements could be made for a closer match to the saturated model.

The parsimony-adjusted measures help evaluate the model's fit while considering model complexity. For the default model, the PRATIO is 0.928, indicating that the model is relatively efficient with respect to the number of parameters. The PNFI (Parsimonious Normed Fit

Index) of 0.773 and PCFI (Parsimonious Comparative Fit Index) of 0.871 are both high, suggesting that the default model balances goodness of fit with parsimony effectively.

The RMSEA (Root Mean Square Error of Approximation) measures the goodness of fit of the model, with values closer to 0 indicating a better fit. For the default model, the RMSEA is 0.042, which is well below the commonly accepted threshold of 0.08, indicating a good fit. The 90% confidence interval for RMSEA ranges from 0.036 to 0.049, further confirming the model’s adequacy. The PCLOSE value of 0.978 suggests a very high probability that the model's RMSEA is close to zero, reinforcing the model’s strong fit.

The HOELTER index is used to assess the sample size adequacy for structural equation modeling. It indicates the minimum sample size required for a stable model fit. For the default model, the HOELTER .05 value is 201, and the HOELTER .01 value is 210. These values suggest that the sample size is sufficient for reliable results. The independence model, however, shows much lower HOELTER values, 36 and 38 for the 0.05 and

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0.01 significance levels. Overall, the default model shows the best fit among the models evaluated, with lower values for fit indices like CMIN and FMIN, and higher values for indices like NFI and CFI, as well as a more favorable RMSEA.

Table 8: Regression Weights: (Group number 1 - Default model) impacts on AI-Integrated Reverse Logistics

			Esti.	Esti	S.E.	C.R.	P
Reverse Logistics Environment	<---	Reverse Logistics	.150	.171	.082	2.094	.036
Return Management	<---	Reverse Logistics	.099	.074	.055	1.350	.177
Return Management	<---	Reverse Logistics Environment	-.107	-.070	.047	-1.492	.136
Performance Effectiveness	<---	Return Management	.053	.094	.121	.777	.437
Satisfaction	<---	Return Management	.088	.148	.118	1.251	.211
Inventory Oversight	<---	Reverse Logistics	.614	1.000			
Integration of Reverse Logistics	<---	Reverse Logistics	.731	1.127	.123	9.185	***
Transport Selection	<---	Reverse Logistics	.713	1.090	.121	9.037	***
Quality Assurance	<---	Reverse Logistics	.678	1.048	.120	8.720	***
Material Breakdown	<---	Reverse Logistics	.690	1.095	.124	8.834	***
Return Insights	<---	Reverse Logistics	.648	.985	.117	8.439	***
Planning System Evaluation	<---	Reverse Logistics	.400	.604	.106	5.678	***
Return Authorization	<---	Return Management	.506	1.000			
Product Inspection and Sorting	<---	Return Management	.703	1.526	.201	7.594	***
Repair, Refurbishment, and Remanufacturing	<---	Return Management	.764	1.662	.211	7.891	***
Repackaging and Restocking	<---	Return Management	.822	1.838	.226	8.124	***
Disposal or Recycling	<---	Return Management	.678	1.444	.194	7.455	***
Legal and Regulatory Compliance	<---	Return Management	.691	1.508	.200	7.529	***
Lean Practices	<---	Reverse Logistics Environment	.687	1.000			
Transport Decision	<---	Reverse Logistics Environment	.774	1.106	.098	11.291	***

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Technical Support Definition	<---	Reverse Logistics Environment	.746	1.028	.094	10.937	***
Environmental Practices	<---	Reverse Logistics Environment	.839	1.203	.100	12.061	***
In-House Expertise	<---	Reverse Logistics Environment	.788	1.117	.097	11.467	***
Third-Party Collaboration	<---	Reverse Logistics Environment	.461	.587	.084	6.979	***
Packaging Strategy	<---	Performance Effectiveness	.805	1.000			
Warehousing Strategy	<---	Performance Effectiveness	.815	1.017	.068	14.907	***
Operational Strategy	<---	Performance Effectiveness	.853	1.086	.069	15.830	***
Location Selection	<---	Performance Effectiveness	.767	.899	.065	13.756	***
Cost Management	<---	Performance Effectiveness	.629	.702	.065	10.749	***
Logistics Network Design	<---	Performance Effectiveness	.755	.904	.067	13.488	***
Risk Management	<---	Performance Effectiveness	.586	.704	.071	9.893	***
Customer Service and Communication	<---	Satisfaction	.709	1.000			
Return Time Value	<---	Satisfaction	.753	.970	.085	11.380	***
Expense Management	<---	Satisfaction	.712	.883	.082	10.799	***
Activity Scheduling	<---	Satisfaction	.696	.882	.083	10.569	***
Information Handling	<---	Satisfaction	.594	.712	.079	9.058	***
Issue & Stakeholder Identification	<---	Satisfaction	.834	1.101	.088	12.480	***
Outsourcing Satisfaction	<---	Satisfaction	.656	.833	.083	9.981	***

The regression analysis demonstrates significant relationships between various constructs and sub-factors in the reverse logistics, return management, performance effectiveness, and satisfaction models. For Reverse Logistics, the sub-factor Reverse Logistics Environment is positively influenced by Reverse Logistics, with an estimate of 0.150 and a p-value of 0.036, indicating significance at the 5% level. Return Management shows no significant impact on Reverse Logistics Environment (estimate = -0.107, p-value = 0.136). Regarding the

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sub-factors, Reverse Logistics exhibits strong positive relationships with variables such as Integration of Reverse Logistics (estimate = 0.731, C.R. = 9.185, p-value < 0.001), Transport Selection (estimate = 0.713, C.R. = 9.037, p-value < 0.001), Quality Assurance (estimate = 0.678, C.R. = 8.720, p-value < 0.001), Material Breakdown (estimate = 0.690, C.R. = 8.834, p-value < 0.001), and Return Insights (estimate = 0.648, C.R. = 8.439, p-value < 0.001). Planning System Evaluation shows a moderate effect with an estimate of 0.400 and a critical ratio (C.R.) of 5.678, with p-value < 0.001.

In Return Management, significant sub-factors include Product Inspection and Sorting (estimate = 0.703, C.R. = 7.594, p-value < 0.001), Repair, Refurbishment, and Remanufacturing (estimate = 0.764, C.R. = 7.891, p-value < 0.001), Repackaging and Restocking (estimate = 0.822, C.R. = 8.124, p-value < 0.001), Disposal or Recycling (estimate = 0.678, C.R. = 7.455, p-value < 0.001), and Legal and Regulatory Compliance (estimate = 0.691, C.R. = 7.529, p-value < 0.001). In Reverse Logistics Environment, Lean Practices (estimate = 0.687, C.R. = 11.291, p-value < 0.001), Transport Decision (estimate = 0.774, C.R. = 11.291, p-value < 0.001), Environmental Practices (estimate = 0.839, C.R. = 12.061, p-value < 0.001), In-House Expertise (estimate = 0.788, C.R. = 11.467, p-value < 0.001), and Third-Party Collaboration (estimate = 0.461, C.R. = 6.979, p-value < 0.001) all have significant relationships. Performance Effectiveness is strongly influenced by Operational Strategy (estimate = 0.853, C.R. = 15.830, p-value < 0.001), Warehousing Strategy (estimate = 0.815, C.R. = 14.907, p-value < 0.001), Location Selection (estimate = 0.767, C.R. = 13.756, p-value < 0.001), Cost Management (estimate = 0.629, C.R. = 10.749, p-value < 0.001), and Logistics Network Design (estimate = 0.755, C.R. = 13.488, p-value < 0.001). Risk Management shows a moderate but significant effect with an estimate of 0.586 and a C.R. of 9.893, p-value < 0.001.

Satisfaction is highly impacted by factors such as Return Time Value (estimate = 0.753, C.R. = 11.380, p-value < 0.001), Expense Management (estimate = 0.712, C.R. = 10.799, p-value < 0.001), Activity Scheduling (estimate = 0.696, C.R. = 10.569, p-value < 0.001), Information Handling (estimate = 0.594, C.R. = 9.058, p-value < 0.001), Issue & Stakeholder Identification (estimate = 0.834, C.R. = 12.480, p-value < 0.001), and Outsourcing Satisfaction (estimate = 0.656, C.R. = 9.981, p-value < 0.001). These findings highlight the importance of reverse logistics, return management, and performance effectiveness practices in shaping customer satisfaction and operational success.

CONCLUSION

The study provides a comprehensive analysis of factors influencing reverse logistics, return management, and operational performance. The diverse sample of respondents—differing in gender, age, experience, industry, role, and familiarity with AI—allows for a broad understanding of the factors at play. The data reveals an even distribution across these categories, with notable concentrations in the e-commerce sector, operational roles, and those engaged in optimized AI processes. This diversity provides a well-rounded foundation for understanding the various factors influencing reverse logistics and related operational outcomes.

The statistical analysis conducted, including the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Test of Sphericity, confirms that the data is well-suited for factor analysis. Factor analysis identifies five key factors that explain a substantial portion of the variance, with the first factor alone accounting for 14.414% of the total variance, highlighting its importance in the context of reverse logistics operations.

Regression analysis reveals moderate correlations between predictors and dependent variables, suggesting that while certain operational factors—such as return time value, outsourcing satisfaction, and warehousing strategy—play a significant role, the models still have moderate explanatory power. The moderate R^2 values indicate that while the models provide valuable insights, there remains unexplained variance, signaling the need for further refinement and consideration of additional factors. The results emphasize the complexity of the relationships between industry-specific variables and operational outcomes, and underscore the necessity of further exploration to fully understand these dynamics.

The impact of lean practices, information handling, and location selection is particularly noteworthy, as they significantly influence experience and age. This suggests that organizational and environmental factors have a profound impact on the operational decisions and strategies within reverse logistics, affecting a range of outcomes across different demographic and professional groups. However, the study also reveals that some variables have weaker or no significant impact, pointing to the complexity of these relationships and the need for a more nuanced approach.

In terms of model fit, the reverse logistics model demonstrates a good alignment with the data, with model fit indices such as CMIN/DF, NFI, RFI, and CFI suggesting that the model appropriately represents the observed relationships. The RMSEA value well below the threshold further supports this alignment, and the parsimony-adjusted measures (PRATIO, PNFI, PCFI) highlight the balance between model fit and complexity, emphasizing the efficiency of the model.

Finally, the regression analysis uncovers significant relationships between reverse logistics constructs, return management practices, and performance outcomes. Key factors such as integration, transport selection, and quality assurance in reverse logistics demonstrate strong positive relationships with sub-factors, while return management practices like product inspection, refurbishment, and recycling have significant impacts on operational efficiency. The study underscores the importance of lean practices, environmental considerations, and third-party collaborations in shaping the reverse logistics environment. Performance effectiveness is found to be strongly influenced by strategic decisions in operations, warehousing, and logistics network design, while customer satisfaction is driven by factors such as return time value, expense management, and outsourcing satisfaction.

Overall, the findings of this study underscore the critical role of reverse logistics in improving operational performance and customer satisfaction. The results also highlight the importance of understanding the various interconnected factors that influence reverse logistics practices and performance outcomes. As the field evolves, further refinement of the models and exploration of additional factors will enhance the predictive power of these analyses, offering valuable insights for practitioners seeking to optimize reverse logistics operations and improve overall business performance.

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