CHEAPER AND BETTER:
OPTIMIZING E-COMMERCE PRODUCT RETURNS MANAGEMENT

by

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SUBMITTED TO THE PROGRAM IN SUPPLY CHAIN MANAGEMENT IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF APPLIED SCIENCE IN SUPPLY CHAIN MANAGEMENT
AT THE
MASSACHUSETTS INSTITUTE OF TECHNOLOGY
May 2022

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ABSTRACT

With the rise of online retailers, people are buying products online more than ever. This has intensified the competition in the e-commerce market. Online retailers are focussing on improved efficiencies in the way they deliver the products with exceptional customer service. Over the past decade, the online retailing industry has come a long way from changing customers' mindset to prefer online buying over buying from physical stores to the prevalent 10-minute deliveries at present. Amid all the innovations in this space, a major cost element of handling product returns usually gets neglected, despite the fact that return costs constitute 10-15% of the overall revenues.

Our research is aimed at helping Lazada group, one of the largest e-commerce players in Southeast Asia, reduce its product return costs. To understand the existing process, we conducted several interviews with the Lazada team. Based on the inputs received from the interviews, we built a Python-based analytical model, encompassing all the logistics and product costs. We validated this model by comparing cost results with the historical data spanning 2021. Once the model represented the reality in terms of product returns and costs, we analysed the current product return process and identified the changes that could help Lazada reduce returns costs. To ascertain whether the recommendations would be effective, we ran several simulations on each of the recommendations, i.e. potential scenarios, to measure their effectiveness. These scenarios included varying the limit for no quality control price, varying the salvage value extracted from the returned products and changing various final decision outcomes. Although this project focuses on Lazada group, this model can be used for optimizing product returns for any online player by simulating various decision nodes and outcomes.

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ACKNOWLEDGEMENTS

We are immensely grateful to our incredible advisors, Dr. Edgar Gutierrez-Franco and Dr. Inma Borrella, for their valuable and constructive feedback throughout this capstone project. We thank them for guiding us, providing us access to relevant supply chain research, and for being truly approachable in an amiable manner. We appreciate them for all their support over the past year and look forward to continuing having them as our mentors professionally and personally.

We would also like to thank our sponsor, Simon Eng, for providing us with high quality and relevant data and guiding us on our project. We would like to thank Dr. Ilya Jackson for helping us with improving efficiency of the algorithm through his valuable advice. A special thanks to Pamela Siska for her tremendous support in editing our drafts, giving meticulous attention to detail.

Thanks to both of our amazing spouses for their continuous support throughout the SCM program and now they know more about e-commerce product returns than they ever wanted to know.

Finally, we would like to thank the SCM program and CTL team for their dedication and hard work to support all members of the SCM class of 2022. This has been an amazing experience for us.

Felicia Chen and Tejinder Singh

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1. INTRODUCTION

1.1 Background and Motivation

Product returns in ecommerce are an inescapable part of business. While this is not a phenomenon exclusive to online retailers, it is one that is far more prevalent for them than for brick-and-mortar stores (Saleh, 2020). This trend shows no signs of abating, looking at the rapid growth of ecommerce sales globally (Samet, 2020).

The consequences to online retailers are significant. Tangible costs are incurred in the form of lost sales and postage monies, as well as costs of collecting and processing returns. Intangible costs include loss of goodwill with customers (Mazareanu, 2021). Collectively, these losses result in lower margins for online retailers. Despite all these significant overheads in form of dealing with returns, retailers are cautious about setting up roadblocks to returns, and sometimes even have return policies that work to the consumer's advantage. Ecommerce retailers therefore try to reduce the cost of returns.

This need to reduce the cost of returns is even more apparent in the Southeast Asian market, where ecommerce companies have made significant investments over the past 10-15 years to compete for customer bases (Ruehl & Sender, 2020). Many companies still remain in the red as a result of these investments and continue to 'dig deeper' to this day, reluctant to compromise on the customer experience (Ruehl & Sender, 2020). Therefore, reducing costs of product returns is a badly needed solution to achieve profitability.

To explore opportunities in this area, this study was done with Lazada Group, a Southeast Asian ecommerce platform based in Singapore, to better understand the potential for cost optimization through product returns management.

1.2 Company Background

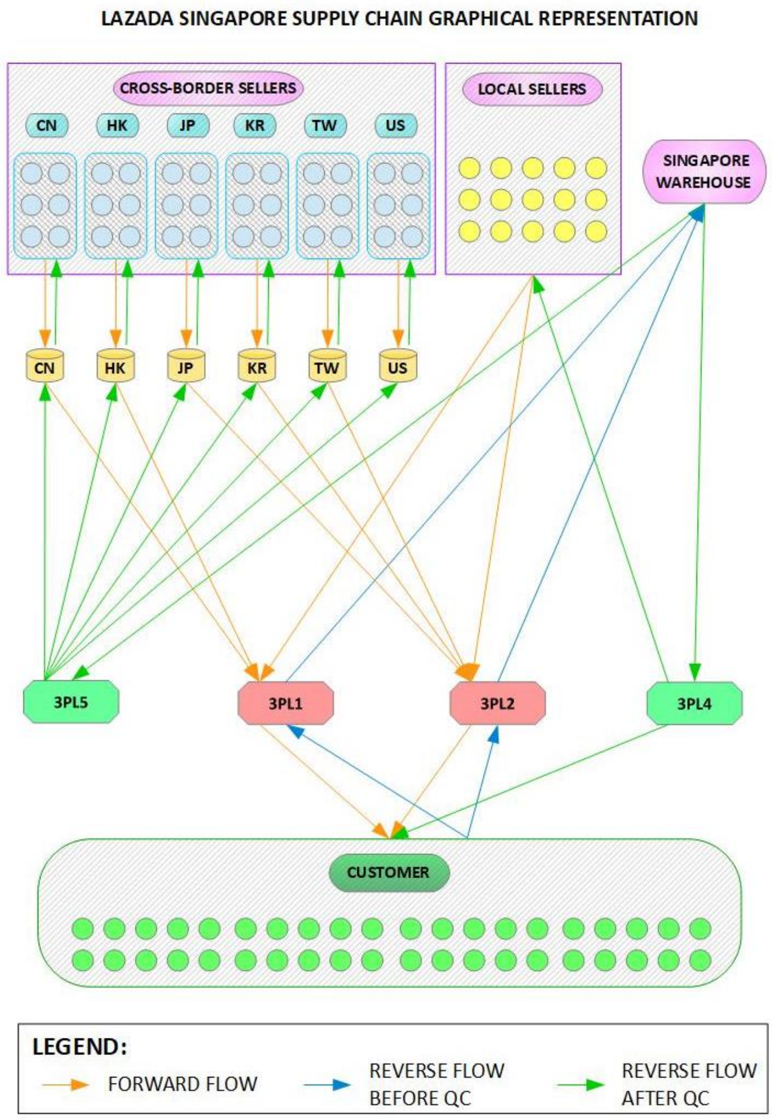
Acquired by Alibaba Group in 2016, Lazada Group is one of the most prominent ecommerce operators in Southeast Asia with more than 50 million active buyers annually. It holds, along with its competitor Shopee, over 70% of the market share in Singapore (Sanchez, 2020).

Lazada operates through 3 main channels for customer order fulfilment and returns: (1) Cross-Border, where products are sold by an overseas seller to the Singapore market; (2) Marketplace, where products are sold by a local seller to the Singapore market; and (3) Retail, where products are stored and sold by Lazada. As discussed in our interviews with Lazada team, these 3 channels generate a combined order volume of 80,000 - 100,000 orders daily, with Cross-Border orders accounting for 53% of orders, Marketplace, 46% and Retail, the last 1%. Across said channels, 800 – 1,000 products per day are returned.

1.3 Problem Description

The first step of the returns process, also known as the first mile reverse logistic flow process, applies across all 3 channels. In this step, 90% of products are sent back to Lazada's warehouse and the rest directly back to local sellers (note: products returned directly to sellers are excluded from the scope of this project as they follow different handling/contracting policies). A product that is returned to the warehouse will first undergo a quality check before a processing decision is made, which can be: (1) send back to the seller for a refund, (2) send to scrap, (3) store and resell, or (4) reject the return request and send back to the customer. Should decision (1) be made, the process differs for each channel. Cross-Border return products will be consolidated, a linehaul arranged and a 3PL contracted to deliver items back to their respective sellers. Marketplace return products will be sent back to sellers through a local 3PL. Retail return products will be restocked and resold to the next customer if they are unopened. A visual representation of Lazada's supply chain is presented in Figure 1.

Figure 1:Process Flow of Logistics Operations of Lazada Singapore



Legend:

CN = China
HK = Hong Kong
JP = Japan

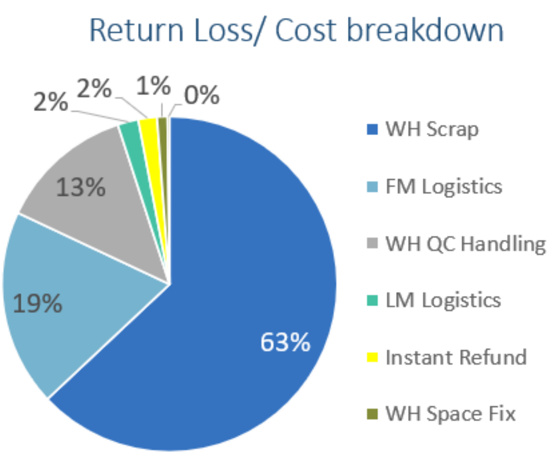
KR = Korean
TW = Taiwan
US = U.S.A
3PLX = 3rd Party Logistics provider.
Each suffixed integer e.g. 3PL5 represents a different provider and is for illustrative purposes.

The high volume of returned products each day, combined with a tedious handling process as illustrated earlier, clearly shows that Lazada has to cope with a significant amount of complexity and cost in the returns process. This complexity and cost are further exacerbated by Lazada's unwillingness to compromise on delivering a positive customer experience, which is a key performance metric and a company value.

1.4 Deep-Dive and Key Research Question

To arrive at a viable research question, the team first conducted a review of costs incurred by Lazada in the returns process. Figure 2 shows a breakdown of costs incurred from April to August 2021. It can be seen that the major cost components are products sent to scrap (63%), first mile logistic cost (19%) and warehouse quality check handling cost (13%), cumulatively representing 95% of the product returns cost.

Figure 2: Return Cost Breakdown for Lazada Singapore (Apr-Aug 21)



A preliminary analysis of the returns data suggests that most returns are incurred from cross-border fulfillment orders (75%), followed by 21% in marketplace orders and 4% for retail orders. The high proportion of cross-Border and marketplace product returns denotes a high cost of return to these sellers.

An exploratory interview with Lazada's quality team revealed that the current product return decision algorithm (i.e., which of the 4 decision outcomes to take) is essentially a simplistic verification process; the reason for return (as specified by the customer in an automated returns system) is checked against the actual product condition post-return. This process, which requires human intervention to avoid adverse customer experiences, fails to consider the many aspects of a complicated supply chain, including the cost of returns for each decision outcome.

To mitigate this problem, this team proposes, as its capstone project, a more sophisticated product returns decision tool, with cost of returns factored into the decision-making process. Some potential features of the tool include:

- Identifying items with a list price lower than the cost of handling its return (i.e., more economically feasible to not collect the returned item than to ship back item)

- Identifying optimal price boundaries of scrapped products that have salvage value and scrapped products that should be discarded with no salvage value.

Therefore, the research question is:

How to improve product return process to reduce cost for an online retailer using a product returns management decision tool?

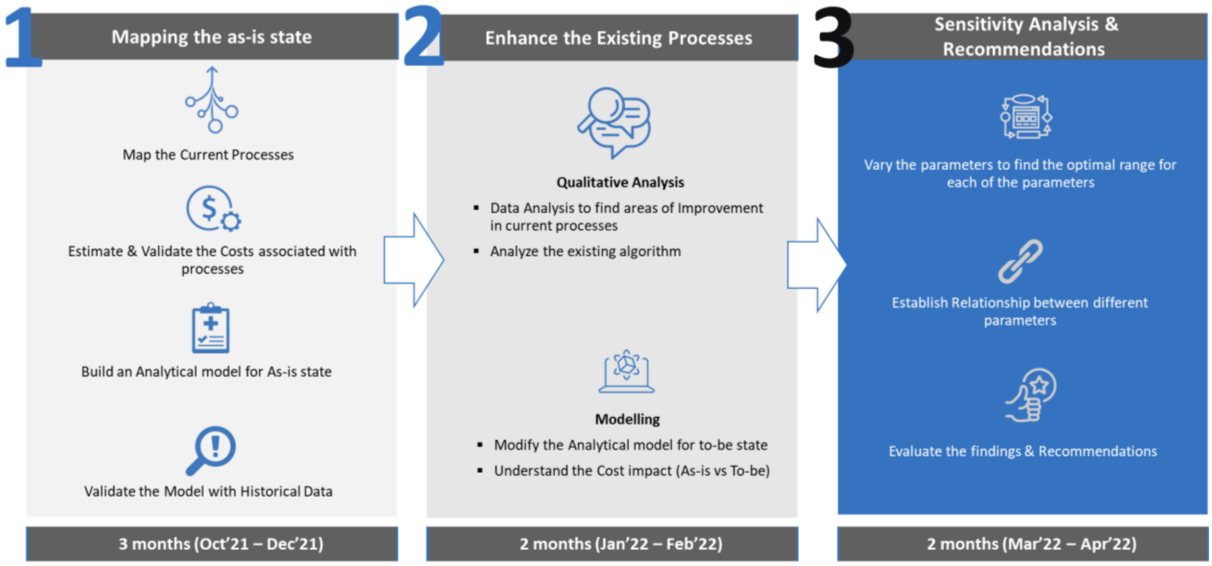
1.5 Overview of Methodology

A 3-phase methodology was adopted, an overview of which is presented in Figure 3. In Phase 1, focus was on understanding the existing processes of Lazada, mapping the key cost components, and modeling the existing process for further refinement.

In the next phase, qualitative and analytical modelling techniques were used to refine the existing algorithms and processes. Existing algorithms and processes were reviewed and modified for better cost efficiency. Then, a revised analytical model was developed to substantiate the changes in terms of cost and return efficiency.

In the 3rd phase, various potential scenarios were analyzed to identify relationships between different process parameters. The results of this analysis were used as a base for building recommendations for Lazada group to hone its product returns process in the last phase, as a value-added step.

Figure 3: Overview of the Proposed Methodology



2. LITERATURE REVIEW

This project develops a viable product returns management decision tool that optimizes the product returns process, thereby reducing costs associated with reverse logistics. This literature review examines studies on the role that product returns play in today's market. A clear understanding of this role was the basis for team's formulation of a decision tool for Lazada.

This chapter reviews the literature pertaining to reverse logistics. Section 2.1.1 investigates the relationship between product returns and customer loyalty, illustrating how product returns play a part in the ecommerce landscape. Section 2.1.2 explores challenges faced while handling product returns to gain insights into obstacles retailers face in drafting return policies. Section 2.1.3 reviews common product return practices and policies in the market. Section 2.1.4 examines current returns handling decision tools in the market to identify common practices. Section 2.1.5 discusses ways to maximize salvaged values from product returns. Finally, a theorized reverse logistic network model is referenced in Section 2.1.6 that serves as a reference for an analytical model. Section 2.1.7 discusses the usage of simulation techniques in testing various scenarios in an efficient manner. Section 2.2 summarizes the literature review and explains the further work that will be carried out in the Capstone project.

2.1 Overview

Research concerning ecommerce has increased in recent years as online retailing gained greater market share compared to conventional retail channels. However, there is still scant focus on ecommerce product returns processes, and to an even lesser extent, how returns are handled. (Asdecker et al., 2017; Walsh & Brylla, 2017) A cost-optimal product returns handling decision tool can provide insights to returns management processes, in turn translating to millions of dollars in cost savings. (O'Connell, 2007) Specifically, Rao et al. (2014) claimed that product returns constitute an average of 22% of the total online retailing amount. Such a percentage clearly indicates huge potential for cost savings.

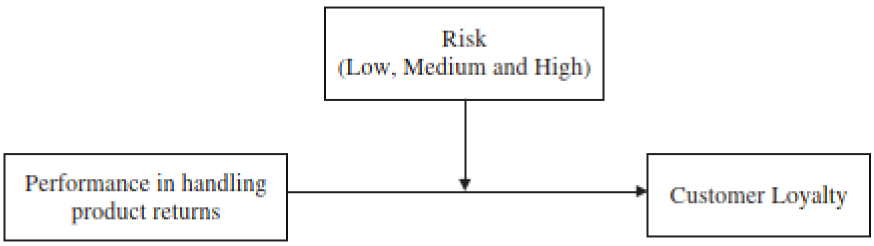
2.1.1 Relationship between product returns and customer loyalty

The relationship between product returns and customer loyalty is first looked at to understand the role of returns in customers' interaction with the online retailer. Li et al. (2013) affirmed a deep relation between product pricing, product quality, return policies and demand. This view is echoed by many others, including Su (2008), who stated that "More than 70 percent of online consumers consider return policies before making purchase decisions." Li et al. (2013) attempted to formulate a mathematical function testing various scenarios for product quality, product pricing, demand and return policies. Their findings suggested various pricing and policy recommendations. High quality products are usually associated with high selling prices and low return volumes. Hence, Li et al. (2013) recommended to have more lenient product return policies for high quality products. For low-quality products, sales can be driven by achieving high sales volumes. When the customer demand is price sensitive, Li et al. (2013) recommended to have low selling prices for products. In contrast, if the customer demand is insensitive to the selling price, lenient product return policies should be deployed.

X. Wang et al. (2017) stated that the customer decision for product returns is largely dependent on the return policies and product types. Based on these factors, two major thoughts for product returns exist. On one hand, firms can make the return processes and policies lenient and focus on enhancing customer experience. But drafting lenient return policies will result in an increased number of returns. On the other hand, firms can devise strict return policies to discourage and limit the losses due to product returns. But in this era of intense competition and product diversification, where customers have unlimited options to choose from, such policies might result in customers switching to other platforms. Hence, we need to find a balance between delivering exceptional customer service and minimizing costs associated with product returns.

Ramanathan (2011) attempted to isolate the performance of companies in accordance with how they process returns and customer loyalty ratings. The framework used is presented in Figure 4. The study defined risk in terms of price of the product and the level of ambiguity in the product specification. High price and high ambiguity items were categorized as high-risk items, whereas low price and low ambiguity items were classified as low risk items. The rest of the items were considered as medium-risk items.

Figure 4: Risk moderating product returns and customer loyalty (Source: Ramanathan, 2011*)*



The study gauged customer responses for product deliveries and returns handling on 10 parameters from 1 to 10, which were later normalized to achieve the aggregated conclusions. The parameters varied from ease of returns, on-time delivery to customer support and payment process, among others.

Ramanathan (2011) used Least squares regression to test various hypotheses. One of the major findings was that ease of returns is an important factor for websites selling either low-risk products or high-risk products. Customers do not spend much time in making buying decisions for low-risk products. With lenient return policies, ease of product returns is an important criterion for choosing an online retailer. Conversely, a lot of research goes into buying high-risk products, suggesting that the reason for returning products relate to real issues with product performance. In either case, the ease with which a retailer handles returns, and processes refunds strongly shape the performance of online retailer by fostering a strong and loyal customer base. Hence, having a well-defined product returns mechanism, along with offering high quality products, is key to achieving success in the times of intense competition where customer has innumerous choices.

2.1.2 Challenges with Product Returns

While having a well-defined product returns mechanism is essential, designing one that is effective is not without its own set of challenges and considerations. The terms of product returns affect many parties and some challenges that e-retailers face with their implementation are as listed.

1. *Costs incurred in collecting returns*

   Collection of returned products is costly; it is fundamentally more complex compared to a forward logistics flow, which Robertson et al. (2020) note is due to being exception-driven and being subject to inconsistent inventory policies. Furthermore, the probability of a product being returned is considerable; Seeberger et al. (2019) found that up to 50% of products sold could be returned with each costing an average of €8. Collectively, a costly process and a high probability of said process being invoked culminate in an astronomical return delivery cost of 1070 billion USD in 2019. (Mazareanu, 2020)

2. *Costs incurred in handling returns*

   Post-collection, products returned need to go through a quality check process to ascertain potential for resale. This process not only consumes time and resources that could otherwise be deployed for other uses, but also suffers from lower efficiency (compared to quality checks for new products). This diminished efficiency can be attributed to lower product volumes, the need for more attention, and the need to re-sort said products. (Robertson et al., 2020)

3. *How to cope with fraudulent returns*

   Fraudulent returns are a plague for online retailers. Bhasin (2019) noted that consumers are increasingly engaging in the fraudulent practice of purchasing products with an intention to return after a short period of use. While some companies such as Amazon, ASOS and Best Buy have taken steps to contain such behaviors by banning customers with excessive numbers of returns, this technique is not without drawbacks; such customers constitute the most profitable consumer group (with more than 3.6 times net sales versus an average shopper (Roshitsh, 2019)), and bans would serve to alienate said customers. Designing a returns mechanism that takes this phenomenon into consideration would be necessary.

4. *Customers are "trained" to return by retailers*

   E-retailers indulge product returns (and the customers who initiate said returns), believing that a lenient product returns policy corresponds to future sales and fosters brand loyalty. However, Robertson et al. (2020) suggest that such indulgent retailer policies, procedures, and marketing efforts around the ease of returns are in fact, exacerbating returns volumes. Through these pursuits, consumers are conditioned to no longer treat reasons-to-return as exclusively limited to defects or mistakes in shipping. This conditioning in turn created reduced consumer commitment to purchase; purchases are now final, only when the item is received and experienced.

5. *Environmental Issues*

Finally, returns are bad for the environment. Approximately 17 billion items are returned annually, amounting to 4.7 million metric tons of additional carbon dioxide emitted every year. (Khusainova, 2019) Aside from the carbon footprint arising from return deliveries, additional energy is also consumed to manufacture more products required to meet the inflated demand from customers buying products with the intention to return. (Khusainova, 2019) When returns are not dealt with appropriately, it may hurt the brand by painting it as environmentally irresponsible. As a case in point, Burberry received a major public backlash when they were found to be burning returned and unsold clothing worth tens of millions of dollars. They claimed that this practice was the industry standard. (Robertson et al., 2020)

Challenges are numerous in dealing with product returns, yet active measures can be sought to address them. As Robertson et al. (2020) observed, some companies have taken an active approach to cut down on returns by adopting the use of technology. For instance, augmented reality technologies, online chatbots and in-store assistants are options to enhance customers' interaction with a product before purchase, thereby reducing the risk of said product being returned.

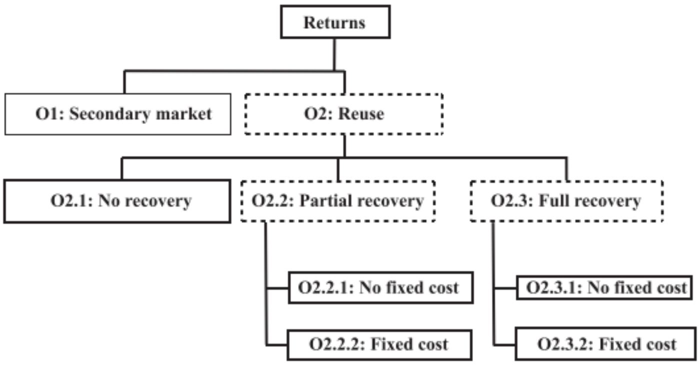
Other companies, such as Warby Parker and Stitch Fix, have attempted a more radical approach by considering product returns as part of the sales process. These firms sent more products to customers than what they expected customers to buy, then encouraged customers to return those that they did not want. (Robertson et al., 2020) Similarly, by allowing customers to return products that are not normally accepted after use, Zappos and Casper used their approach in product returns to gain a competitive advantage over competitors. (Toft et al., 2022)

Such mitigations indicate that a good product returns policy must consider the challenges associated with implementing said policy and take appropriate actions in anticipation.

2.1.3 Product Return Policies

Vlachos & Dekker (2002) discussed that most online retailers provide an option for customers to return products. The reason for providing options could be due to a need to comply with local regulations or an effort to gain customers' loyalty and trust. To maximize the profits for online retailers, they carried out a study on a single period inventory model, where focus is on optimizing order size. Focus is to utilize the return orders to a maximum extent to meet the demand of customers in a single period. This study can be extended to various fashion-related items whose demand tends to be dynamic. Vlachos & Dekker (2002) stated that there are 6 potential options for a retailer when a return is initiated by the customer, as shown in Figure 5.

Figure 5: Options for handling returns (Source: Vlachos & Dekker, 2002)



The first option is to sell the product in the secondary market. According to Vlachos & Dekker (2002), this option should be exercised when the lead time for product recovery is long. Since the demand is to be met for a single period, the product might not be recovered in time for reuse. Options to reuse the product are further bifurcated with the most prominent one being the option of "No recovery", which is suitable for products that can only be reused if not opened. Other cases include full product recovery and partial product recovery. They are further narrowed down based on their fixed cost, where usage of specific machinery for repacking returns might be significant. Vlachos & Dekker (2002) further built these options into a mathematical model to arrive at the ideal initial order quantities for single-period products with random demands.

Several other retailers adopted various strategies to offset the impact of product returns. As per Seeberger et al. (2019), looking at a holistic picture by combining the dual objective of reducing the returns and salvaging the returned products can provide better profits to the online retailers. Almost 67% of online retailers have been unsuccessful in decreasing the return rates and properly salvaging the returns. Retailers have limited flexibility in impacting the volume of returns apart from ensuring products are high-quality, but they do have 3 major opportunities for salvaging the product returns. As per Seeberger et al. (2019), online retailers can either sell the products in primary market, secondary market or return the products to manufacturers. But the most exercised option even today is to sell the returned product into primary markets. This strategy is suboptimal since it devoid the retailers of the potential opportunity to generate more revenues from the returned products. They quoted an example of Zalando, which salvages the products in primary market as well as in self-owned secondary market. They own 3 physical outlets and a Lounge, an online platform specifically for selling discounted and overstocked goods. Maximizing profits from salvaging returns will be discussed further in the section 4.4.

In all, these strategies and multi-channel selling approach ensure that online retailers stay competitive in the existing market where customer has no lack of options to buy products from.

2.1.4 Cost Recovery/ Salvage Value

Roellecke & Huchzermeier (2017) discussed the retailer's optimal return policy with endogenous salvaging modeled as an interaction effect between the primary and secondary market. They studied the resulting profit improvement based on a 10-50% performance improvement for different investment types and their results are tabulated in Figure 6. Salvaging condition is labelled as “limited” when salvaging value is less than cost and labelled “affluence” when salvaging value is greater than or equal to cost.

Figure 6: Avg. profit increment as per investments (Source: Roellecke & Huchzermeier, 2017)

Investment type	Salvaging condition	% change 10	20	30	40	50
Decrease rate of returns	Limited	2.8	5.7	8.6	11.5	14.5
	Affluent	10.2	22.1	36.2	53.6	76.0
Increase branding	Limited	2.1	1.8	−1.1	−6.5	−14.5
	Affluent	3.2	3.9	2.0	−2.6	−9.8
Increase information provision	Limited	0.8	1.6	2.5	3.5	4.4
	Affluent	9.7	21.2	35.3	52.5	74.1
Reduce cost of recovery	Limited	10.1	20.7	31.8	43.4	55.9
	Affluent	44.0	125.1	157.9	167.0	176.5
Improve salvaging	Limited	1.6	3.3	5.1	7.0	9.1
	Affluent	67.1	137.3	140.3	144.0	151.3
Reduce return uncertainty	Limited	−0.4	0.8	2.0	3.4	5.0
	Affluent	23.2	59.5	131.6	138.7	140.1

Seeberger et al. (2019) looked at the profit-maximizing allocation of returns to the primary market, secondary market and return to manufacturer, and studied the combinatory effect of returns management and salvaging with considerations of endogenous salvage values along with external factors. They concluded that a smart salvaging strategy optimally distributed across the 3 salvaging channels: (1) primary market; (2) secondary market; and (3) return to supplier, increase profit by more than 90% as compared to offering free returns and salvaging exclusively in the primary market. While reselling in the primary market is the most common practice and perceived to generate the highest revenue, Seeberger et al. (2019) argued that several factors worked against salvaging exclusively in the primary market. First, prices in the primary market need to be reduced to increase demand and accommodate an increase in supply from the returns. Next, returns sent back to the primary market requires high refurbishment cost. Third, salvaged returns risk being returned for a second time when sold through the primary market. Lastly, reselling through the primary market risks cannibalizing initial product sales.

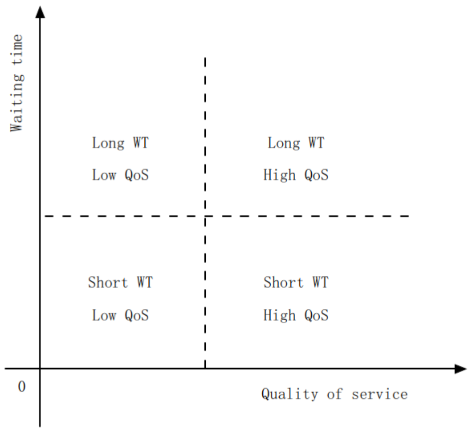
In general, Roellecke & Huchzermeier (2017) advocate that there are 2 return strategies that are both profitable and can be undertaken. One is to have strict restrictions around salvaging, accompanied by lenient return policies. This return policy is exemplified in the case of Zalando, as mentioned in section 1.4, where Zalando has lenient return policy, but exerts strict control over its secondary market, limiting it to less than 1% of its overall sales. This strategy keeps its salvage value above production cost, enabling Zalando to achieve high profit and market share. An alternative strategy is to have unrestricted salvaging with strict return policies. As a case in point, Amazon has few restrictions on its secondary markets, reselling all its returns solely through them. It, however, constrains its return volume by deterring customers from returning via restocking fees. Customers who were found to have excessive returns were also banned from its platform. Seeberger et al. (2019) surmised that both strategies can be profitable. However, the former is both more profitable and customer-friendly and would be preferred over the latter in direct competition.

2.1.5 Product Return Decision tools

In view of the challenges faced in processing returns, including return frauds, false ordering, and other malpractices, online retailers have been compelled to adopt a decision matrix that provides a standard processing framework once a return request is initiated by the customer.

Numerous studies in the past to define such a matrix for processing product returns. W. Wang (2015) proposed a method to process the product returns by providing a decision on whether to accept the returns based on the customer behavior. The major input for this study was the customer segmentation based on their sensitivities to waiting time and quality of service. The customer segments have been illustrated in Figure 7. Some customers look forward to the resolution of their return request within the least possible time whereas others focus on the quality of service.

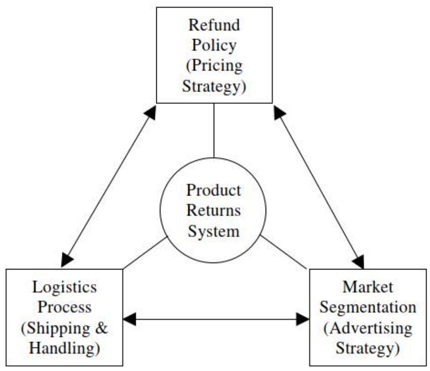
Figure 7: Customer segmentation based on time and cost requirements (Source: W. Wang, 2015*)*



Following that, based on the time and cost sensitivity, the model tries to generate time and cost specific indices, which help to optimize and provide the decisions to be taken for each subset of the customers using Lagrange functions. The model was tested on a sample case study where the interview of 150 customers was analyzed based on their responses to these critical factors.

Other studies tried to optimize the returns process by looking at the product returns system holistically. Yalabik et al. (2003) called out a need to look at the product returns process at a strategic level, which in turn requires strong co-ordination between the logistics and marketing arms of a firm.

Figure 8: Integrated product returns system (Source: Yalabik et al., 2003*)*



An integrated product returns system has three major components: a robust refund policy, efficient reverse logistics process and well-devised marketing strategy. Yalabik et al. (2003) aimed at developing and analyzing a model over two set of customers: customers whose expectations were met and customers who were unsatisfied with the product quality. A series of potential scenarios were tested where they evaluated the product utility for both retailers and customers. They arrived at an important insight: whenever the retailer fails to integrate the marketing and logistics efforts, it will under-invest in the department that is less politically powerful. This distorted balance in the spends for both the departments impacts the bottom line, causing potential revenue losses for the retailer.

2.1.6 Reverse logistic network model

Reverse logistics network model often involves deciding the location of various echelons such as facilities, warehouses, and processing centers. Most of the research available around reverse logistics network model involves network optimization focusing primarily on the long-term objectives of identifying the locations that would lead to minimized logistics costs. X. Wang et al. (2017) focused on designing the three-echelon product returns network comprising of initial collection points (ICPs) and centralized return centers (CRCs). Their objective was to develop a mixed integer non-linear programming model that would aim to minimize the total reverse logistics cost of the network. The model was designed to optimize the location of ICPs that would justify enough return volumes that could be aggregated and sent to CRCs in large shipments in given timeframes. This research focused entirely on the strategic decision of identifying the optimum locations for ICPs and CRCs. But such decisions are rarely taken in isolation. There is a need to couple them with tactical and operational decisions.

Salema et al. (2007) attempted to design a generic framework that encompasses both strategic and tactical decisions while deciding the locations of nodes. The model considers a separate time modelling component along with the network modelling. This provides flexibility to determine the production and inventory levels along with the network design. It considered a four-echelon generic end to end closed loop supply system which was later tested on a generic case of a Portuguese company.

Gutierrez-Franco et al. (2009) have also adopted linear programming to minimize the total logistics cost for a network considering intermediate production processes in the semi-integrated steel industry. This three-echelon network structure first formulizes a generic model using Generic Algebraic Modelling System (GAMS) through CPLEX® solver. which is later focused on Colombian steel industry, which employs semi-integrated process for production of almost 65% of its steel. Since the semi-steel industry is built on recycled steel waste, the model considers a separate echelon for collection of scrap as the raw material for processing steel. The model minimizes the overall logistics costs that include raw material acquisition costs, transportation costs, inventory holding costs and production costs.

In all, the papers emphasized the importance of considering all involved costs in total reverse logistics process, be it inventory holding costs, reverse product acquisition costs, or any other associated cost. Also, almost all papers that models the reverse logistics network model uses a prescriptive optimization model.

2.1.7 Simulation in Reverse logistics

Reverse logistics becomes more prominent for online retailers considering the uncertainty in product returns. Product return volumes vary across months due to the dynamic seller and customer interactions. Since most of the online retailers are working on marketplace model where customers have the independence to choose product supplied by various sellers, product returns vary by category, product type, price, geography, and several other factors across months. To capture the uncertainty of demand for online retailers and more so for the product returns, many studies have tried to utilize simulation methodologies to test the efficacy of various scenarios to bring efficiencies in the product return policies and processes.

Muir et al. (2019) analyzed the impact of these uncertainties on the inventory and performance of online retailers. They conducted analysis on consumer durable and nondurable goods data of a large US retailer. Various scenarios were run on a multi-echelon inventory model by considering three major sources of variation on product returns. In the first scenario, they simulated the inventory model separately for centralized and decentralized return systems. In next scenario, they introduced cross-channel returns policy where a customer had the flexibility to buy and return a product through different channels as per the convenience. The last scenario included introducing seasonal variations in the product demand causing the returns to differ across categories and months. They identified a strong correlation between inventory levels and changes in returns policies suggesting the need for interlinked product demand, network design and return policies.

Pishvaee et al. (2009) tried to optimize the location of collection/ inspection, recovery, and disposable facilities for a multi-stage reverse logistics network by using efficient simulated annealing algorithm. This algorithm is further helpful to refine the location of facilities based on strategic decisions by simulating the priorities given to various activities. Since the returned products differ in their characteristics, the need for inspection and collection differs across products to define the outcome i.e., scrap or salvage the product. The simulated annealing method on top of MILP optimization helped ease out the case due to the quantum of the volumes. There have been several attempts to simulate various scenarios to arrive at the decisions in a much quicker and efficient way. Some researchers have even attempted to refine the outcome using simulation in case of large datasets where optimization proved to be sub-optimal. This provides an initial direction that simulation can prove to be an important tool to test various recommendations.

2.2 Conclusion

Existing research on product returns for online retailers suggests that there is a strong relation between the product return experience and customer loyalty. Hence, firms are looking to maintain a balance between delivering product returns and delivering exceptional customer experience by having prudent return policies, even attempting to draft different policies for different segments of customers based on their behavior. While product returns can be challenging to handle, they can be positioned as an alternative avenue to increase customer engagement when incorporated as part of the business strategy. A good returns salvaging strategy is therefore vital to maximize profits and should include the consideration of primary markets, secondary markets and return of product to suppliers. The impact of return salvaging on market equilibrium should also be considered. Additionally, there have been various studies on optimizing the reverse logistics for products across industries.

Lazada Group currently adopts a decision matrix consisting of various checkpoints, guiding the company towards different decision outcomes that can be taken for a particular returned product. These options include scrapping the product, returning the product to the seller, customer or reselling the product. With these various options, there is a need to encapsulate all the costs associated with the return of a product into the design of the product return decision tool for greater cost efficiency. With Lazada sending a high proportion of returns to scrap today, it is also imperative to consider maximizing cost recovery from scrap products in the secondary market in the project. Since Lazada's business model has a limited primary market with third-party sellers owning most of it, concerns of impact on the primary market are diminished.

The reverse logistics network models examined in section 2.1.6 provided a reference for building an analytical model for Lazada. However, these research papers referred focused on reducing logistics cost using various optimization techniques. There is a lack of research on modelling end-to-end decision-making tools that would help ecommerce players decide on decision outcomes for returns.

In addition to filling the gap for end-to-end decision-making tool, this capstone project also provides fresh insights into managing product returns where third-party sellers are involved. This study fills a gap in the current literature, which has largely focused on retailers without third parties.

3. RESEARCH METHODOLOGY

Lazada seeks to lower expenditure on handling product returns through a more cost-efficient return process and decision algorithm. To decide on the return process and decision algorithm, a decision tool is proposed. This decision tool should be able to capture all cost aspects of product returns process to reflect the total cost of returns for any given month.

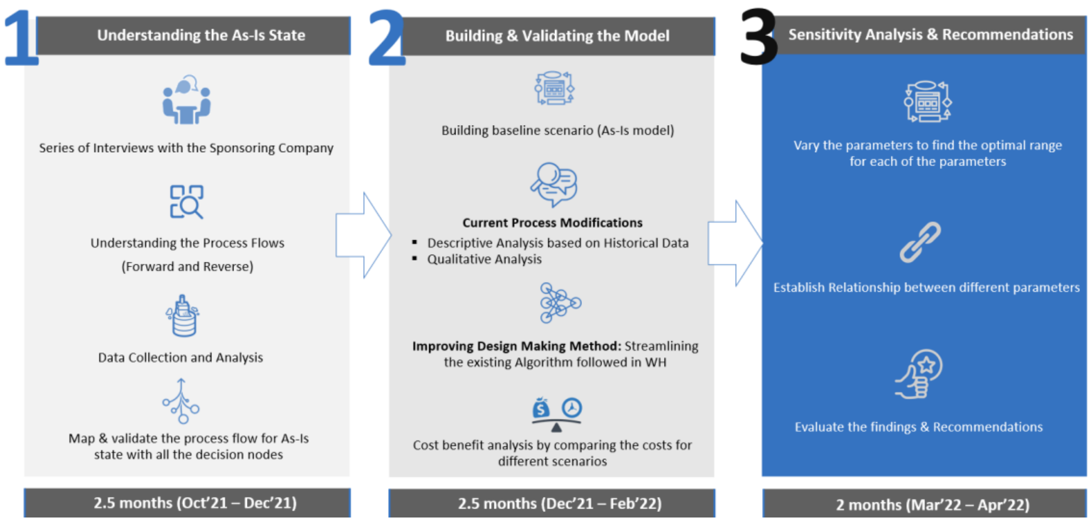
While most reverse logistics network models reviewed in section 2.1.6 use optimization model, it was not the ideal type of model to be used for this project. This is because in the case of Lazada, the forward and reverse logistics as well as quality check process are handled by third-party vendors. Hence, there are no resource constraints that would require optimizing returns based on costs associated with each of the steps. Considering optimization solely based on cost parameters also risks neglecting the customer service focus.

To ensure a balance between maintaining customer satisfaction and reducing costs for product returns, there is a need to adopt an alternative model that collects cost-of-returns data from the decision matrix outcomes. Moreover, Lazada's existing decision parameters defining the decision matrix are based solely on user experience and not backed by any quantitative analysis. Since the return process is dynamic with many possible decision paths, the type of model chosen should be robust enough to cater to this process.

Hence, a combination of qualitative analysis and simulation model is proposed. Qualitative analysis allows for the consideration of customer preferences which would inform the synthesis of the model. The model would in turn provide insights on (1) reduced-cost product flow paths and how (2) individual parameters affect costs of returns. Cumulatively, a viable decision tool that reduces cost of returns will be derived, thereby answering the research question posed.

This section discusses the approach taken to address the main research question of how cost of returns can be reduced by using a decision tool to assist in product returns process design. The methodology for this approach is illustrated in Figure 9 and detailed after.

Figure 9: Methodology



The capstone project methodology was approached in 3 main phases:

(1) Understanding the as-is state

(2) Building and validating the model

(3) Sensitivity analysis and recommendations

In the first phase, product returns process flow and decision algorithm for existing operations of Lazada group were mapped. Through a series of interviews with the sponsoring company, data was collected and analyzed. An existing operations process flow was then drawn up with existing costs associated with each of the processes included in the flow.

Next, in phase 2, the processes mapped in phase 1 were built into a simulation model as a baseline scenario. The model was run with historical returns data for the past 12 months and compared to actual cost of returns for model validation. The current process flow and decision algorithm were also reviewed and redesigned using qualitative analysis to be more cost-efficient. A revised simulation model for the redesigned process flow and algorithm was then built. Cost of returns results from the revised simulation model were compared against the results of the baseline scenario to evaluate the effectiveness of the redesign.

Finally, in phase 3, sensitivity analysis of each parameter was conducted. This was done by analyzing the cost of returns when varying a parameter in the simulation model. Their cost-optimal range and changes relative to other parameters were also examined to establish relationships between the different parameters. Recommended range of value for each parameter can then be made through these understandings.

In essence, this simulation model will be a useful tool in product returns management. The model can be used to assist in the designing of product returns processes and decision matrix, with an overview of returns cost impacts. Beyond the scope of the project, the model will also allow for a quick and efficient proof-of-concept to verify strategic decisions changes and assess their impacts on cost of returns.

3.1 Understanding the As-Is State

The first phase of the methodology involved understanding the current return processes. This understanding was crucial for recognizing gaps in the existing processes and identifying plausible areas of improvements. This was achieved through a series of interview with the sponsoring company, current process flow mapping and historical returns data collection.

3.1.1 Interview with Sponsoring Company

A series of interviews were conducted with Lazada to understand the current return process flow. Product return process comes under the charge of the Quality Assurance department in Lazada Group. Hence the interviews were conducted with Mr. Simon Eng, the Vice-President of Quality Assurance for Lazada Singapore and RedMart, and his team members.

3.1.2 Current Process Flow Mapping

These interviews were helpful to study the existing product fulfilment and product return processes. Various insights including costs associated with each of the processes, difficulties in existing operations and areas of improvement were generated through these discussions. Building on these discussions, additional interviews with Mr. Simon Eng and his team were conducted for details of specific operations if required.

3.1.3 Historical Returns Data Collection

To work out the associated cost for each process and to identify areas for improvement, Lazada provided the product returns data for year 2021 for an initial analysis. The returns data can be found in Appendix D. The data contained the following main data fields:

Product Details: The fields providing details on the returned product include:

- Product Name
- Product Description
- Product Category
- Product unit price
- SKU
- Actual Serial Number

Return Details: Details pertinent to the return process are available under return details. The main fields are as below:

- Return initiated Date
- Inbound Return Operator Name
- Inbound Batch ID
- Inbound Tracking Number
- Inbound Date
- Return Number
- Platform Return Item ID
- RMS Return Item ID
- Status
- Customer Return Reason One
- Customer Return Reason Two
- Customer Comment
- Logistics Closure Data
- Logistic Closure Outcome
- Logistic Closure Return Operator Name
- Cancelled Date
- Handover Tracking Number

Seller Details: Details on the seller of the product, including geographical and contact information, are available in the dataset:

- Seller Name
- Seller ID
- Seller Code
- Seller Country
- Seller email

Order Details: Product order details with the following fields are available:

- Fulfilment Type
- Handover At
- Customer Order Number
- Box ID

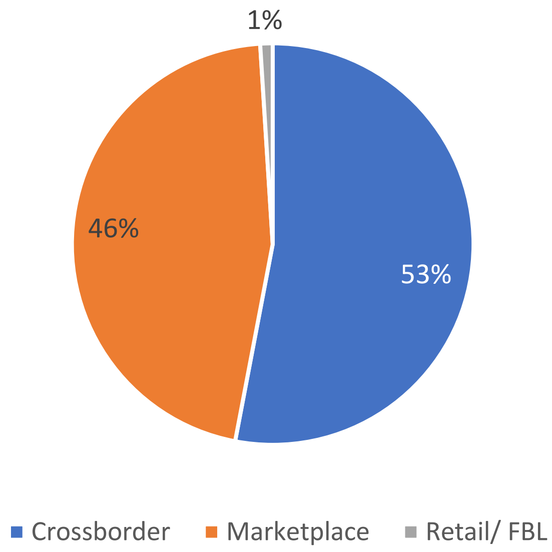
Quality Check Details: Quality check details, including inferences of product return reasons are given:

- QC Center Name
- QC Date
- QC Result
- QC Return Operator Name
- IMEI/Serial Number matched
- Reasonable Doubt

- Customer Claim Valid or not

Additionally, Lazada provided monthly sales volume percentage through each channel in Figure 10.

Figure 10: Monthly sales volume percentage through each channel



3.2 Building and Validating the Model

After the current product return process and decision algorithm were mapped, a simulation model was built to verify the algorithm's accuracy. Then, the current return process and decision algorithm were enhanced: major cost components were first identified, and modification efforts were focused on reducing these identified cost components. The enhancement exercise was performed separately for current returns process flow and the decision matrix.

3.2.1 As-Is Simulation model

Variables used in the model are discussed below.

<u>Shipping Cost</u>

The shipping cost from customer to warehouse, $Shipping\ Cost_{CW}$, used is attached in Appendix A. Rate for shipping is based upon the gross weight of parcel.

The shipping cost from warehouse to seller, $Shipping\ Cost_{ws}$, used is similarly attached in Appendix A. Rate for shipping is similarly based upon the gross weight of parcel.

<u>Quality Check Cost</u>

Cost of quality check, $Cost_{QC}$, for each item inspected would have to be determined. Depending on the nature of the cost, duration of time spent on each item for different product type may need to be considered.

Refund to Customer

When a return is accepted, the cost paid by buyer for the returned item will be refunded to buyer. A return is accepted if the decision outcome is not "Return to Customer". This cost is the listed price of product on Lazada platform, less any discount from vouchers or promotions, plus the cost of forward logistics charged to buyer.

$$Refund\ to\ Customer\ = Product\ Listed\ Price - discount + Forward\ Shipping\ Cost \quad (1)$$

Refund from Seller

When a return is sent back to seller, the cost paid by Lazada to the seller for the returned item will be refunded to Lazada. This cost is the listed price of product on Lazada platform, less any discount offered by seller and less the cost of forward logistics charged to seller.

$$Refund\ from\ Seller\ = Product\ Listed\ Price - discount - \ Forward\ Shipping\ Cost \quad (2)$$

Salvage Value

Products in sellable condition after the return process can be sold to a secondary market for salvaging. The amount received from salvaging in the secondary market is defined by a percentage parameter, S_1. Products must have gone through the quality check process to determine its condition before it can be sold in a secondary market. Equation 5 will be used to calculate the salvage value of products in the secondary market.

$$Salvage\ Value\ = Product\ Listed\ Price\ x\ S_1 \quad (3)$$

Cost of Returns

The cost of returns for each returned item will be calculated by summing each cost component listed in Table 1 according to its respective decision outcome.

Table 1: Cost of Return for each decision outcome

Decision Outcome	Shipping Cost from Customer to Warehouse	Cost of quality check	Shipping cost from Warehouse to Seller	Refund to Customer	Refund from Seller	Product Salvage Value
Sent to Scrap	$Shipping\ Cost_{CW}$	$Cost_{QC}$	-	$Product\ Listed\ Price$	-	$Product\ Listed\ Price\ X\ S_1$
Return to Customer	$Shipping\ Cost_{CW}$	$Cost_{QC}$	$Shipping\ Cost_{ws}$	-	-	-
Return to Cross-Border Seller	$Shipping\ Cost_{CW}$	$Cost_{QC}$	-*	$Product\ Listed\ Price$	$Product\ Listed\ Price$	-
Return to Local Seller	$Shipping\ Cost_{CW}$	$Cost_{QC}$	$Shipping\ Cost_{ws}$	$Product\ Listed\ Price$	$Product\ Listed\ Price$	-
Return to Warehouse	$Shipping\ Cost_{CW}$	$Cost_{QC}$	-	$Product\ Listed\ Price$	$Product\ Listed\ Price$	-

Note:
**There is no shipping cost from warehouse to Cross-Border seller as this cost is not under the purview of the QA department and will not be included into the calculation of cost of returns.*

3.2.2 Model Validation

After completing the simulation model, the model was run with returns data of the past 12 months to test for its accuracy. The total return cost generated from the simulation model was compared to the total cost of returns recorded by Lazada. If the results from the simulation model follows closely to the actual returns cost, the model is validated and phase 2 can commence. Otherwise, current return processes will have to be verified with Lazada and simulation model checked to ensure that it correctly reflects the current processes. This process was repeated until the model is validated.

3.2.3 Clean-up of Existing Decision Algorithm

Before developing alternative scenarios, an additional step of cleaning up existing algorithm was required. From the existing algorithm shared by Lazada earlier in section 3.1.3, some parameters originally used in the algorithm were no longer in use. Hence paths in the existing decision algorithm that use the obsolete parameters had to be removed or their decision nodes were removed. Results of the cleaned-up model were then considered as the baseline scenario for comparison with future alternative scenarios developed.

3.2.4 Current Process Modifications

Using existing process flow and decision matrix, a detailed analysis of all decision nodes was conducted with actual product returns data. Following that, a qualitative analysis of existing processes and algorithm was done, and several process flow modifications were proposed through developing alternative scenarios to examine opportunities to lower cost. Paths of the algorithm were also reviewed to assess its relevance and revised to reduce overall returns cost while not compromising on customer's experience.

3.2.5 Comparing results of existing and optimized process

Each alternative scenarios developed had its revised process and algorithm implemented individually into the simulation model developed earlier in section 3.2.1. Total return cost using returns data of the past 12 months was then generated for the alternative scenarios, compared against the result from baseline scenario and evaluated.

3.3 Sensitivity Analysis and Recommendations

3.3.1 Sensitivity Testing

A series of sensitivity tests can be performed using the revised simulation model to determine an optimal range for each parameter. Identifying a range for the parameters with their cost impacts would be very useful to Lazada to determine the final parameter value to adopt. The flexibility would also allow factoring of other considerations such as customer experience and seller engagement into the adoption.

Sensitivity testing was performed on all variable parameters. All the parameters were simulated over a range using return products data for the past 12 months. The results were then plotted in a chart and evaluated for their most optimal range.

A similar approach was taken for the decision algorithm. Algorithms with alternative routings can be run with the simulation model. Their results were then compared to the baseline result for evaluation. This was useful in understanding the cost trade-off while making strategic decisions.

3.3.2 Relationships between parameters

Relationships between the parameters can also be established in this phase when observing how the change in one parameter impacts another. In this phase, sensitivity analysis of each parameter would be conducted to better understand the relationship between different process parameters. This understanding will be instrumental in defining the cost-optimal range for varying each of the parameters without impacting the overall cost for each of the selling channels.

3.3.3 Recommendations

Once the impact of varying various parameters within the optimal range is understood, the cost trade-off for taking various strategic decisions can be calculated from the results. These would form a part of the recommendations for Lazada group to optimize its product returns in the last phase, as a value-added step.

4. RESULTS

This chapter explains the findings of the study. Section 4.1 briefs the understanding of current state through series of interviews that we conducted. These interviews helped us map the existing process flow and gauge the challenges. Section 4.2 explains how we built and validated the model. After building the model, Section 4.3 explains the sensitivity analysis that we conducted to arrive at various results. This chapter is concluded with Section 4.4 that explains various use cases that Lazada can leverage to maximize the salvage value from scrapped products.

4.1 Understanding the As-Is State

4.1.1 Insights from the Interview with the Sponsoring Company

An interview was conducted with Simon Eng on October 1, 2021, for an overview of Lazada Group. Through the interview, we learned that the business strategy that Lazada adopted in the Southeast Asian (SEA) market was to convert more buyers from offline mode of purchase to online by providing better return experience since buyers are unable to see, feel or try the physical item before making any purchase decision. This strategy was adopted due to the company's value of 'Living Customer First' as well as the intense competition in the SEA market. Return policies were relaxed, loosely regulated, and customers' experience on the platform is prioritized over profitability. However, such an approach is not scalable, as customers found many loopholes to abuse the refunds process. Hence, Lazada is looking to make business more sustainable in today's market. A detailed record of the interviews can be found in Appendix B.

This strategy resulted in a high daily volume of returns to be handled. As one of the 2 largest ecommerce platforms in Singapore, Lazada currently has a daily order volume between 80,000 to 100,000 in the nation. As per our discussion with the team, we found that, of these orders, the return rate ranges between 1.02 to 1.05%. This figure translates to an estimated 1,000 returns to be handled every day, which becomes a key lever for improving the scalability and sustainability.

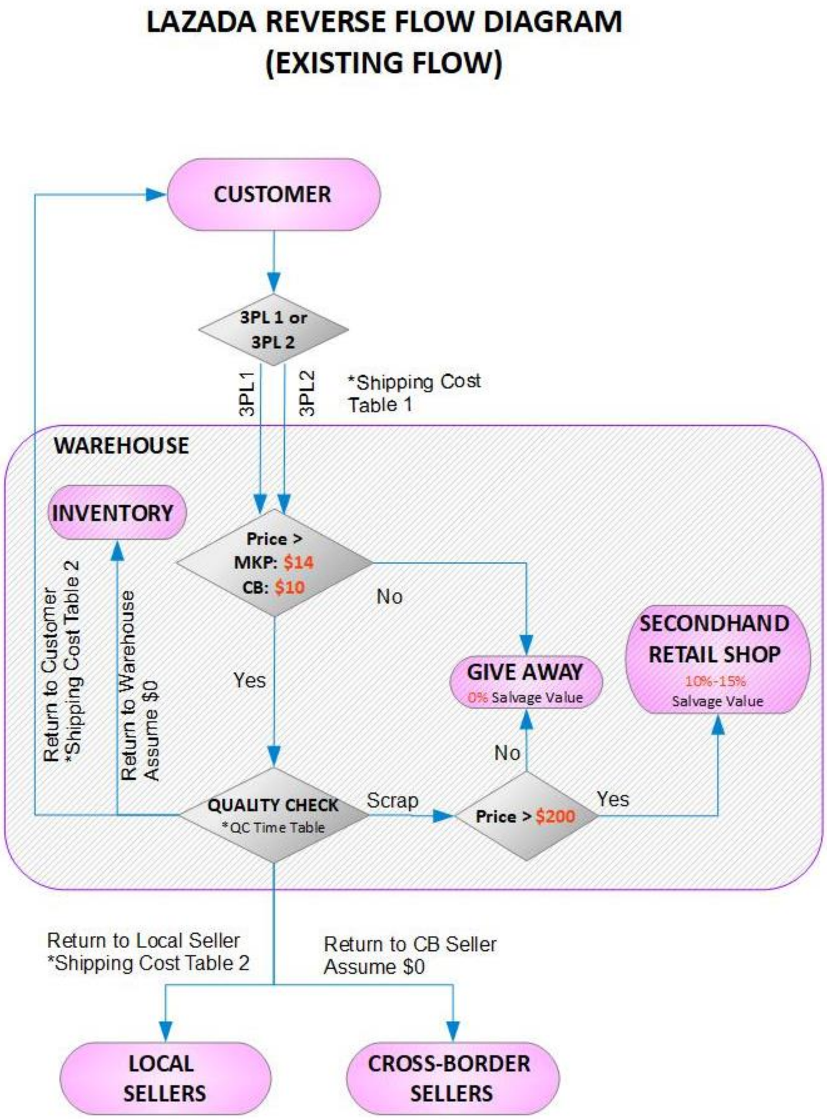
Despite the high volume of returns, Lazada expressed their reluctance to reduce the number of returns through implementing a more stringent return policy. They viewed such an action as going against their core value of Living Customer First as well as the strategy of gaining market share though providing the best service.

The Quality Assurance department also carries the responsibility of optimizing product returns cost. As shown in Figure 2, the major cost components in the existing cost of returns resulted from the high volume of product scrapped, cost of first mile logistics, and the cost of quality check for returns. To lower overall cost of returns, a better product return process is necessary to mitigate the high cost of returns that result from a relaxed return policy. The current returns process will be examined next for optimization.

4.1.2 Mapping of Current Process Flow

To study the current return process, a second interview was conducted Mr. Simon Eng. on October 22, 2021. The detailed interview can be found in Appendix C. Based on the interview, the current return process was mapped as shown in Figure 11.

Figure 11: Current Return Process Flow for Lazada (Rhombus represents a decision node)



1st Decision Node: First Mile Logistics

Two third-party logistics (3PL) companies facilitate returns for Lazada. They will be referred to as 3PL1 and 3PL2 hereinafter. The two 3PLs collect returns from customer and deliver them to Lazada warehouse. 3PL 1 has the option for customer to have a pick-up arranged with a courier or to drop-off their items to a drop-off station. 3PL 2 offers only drop-off service.

After a customer initiates the return process on Lazada App/website, they can choose from one of the following options to return their items:

a. Pick-up by 3PL1
b. Drop-off by 3PL1
c. Drop-off by 3PL2

Delivery charge for each item is determined by their weight and whether pick-up/ drop-off was chosen.

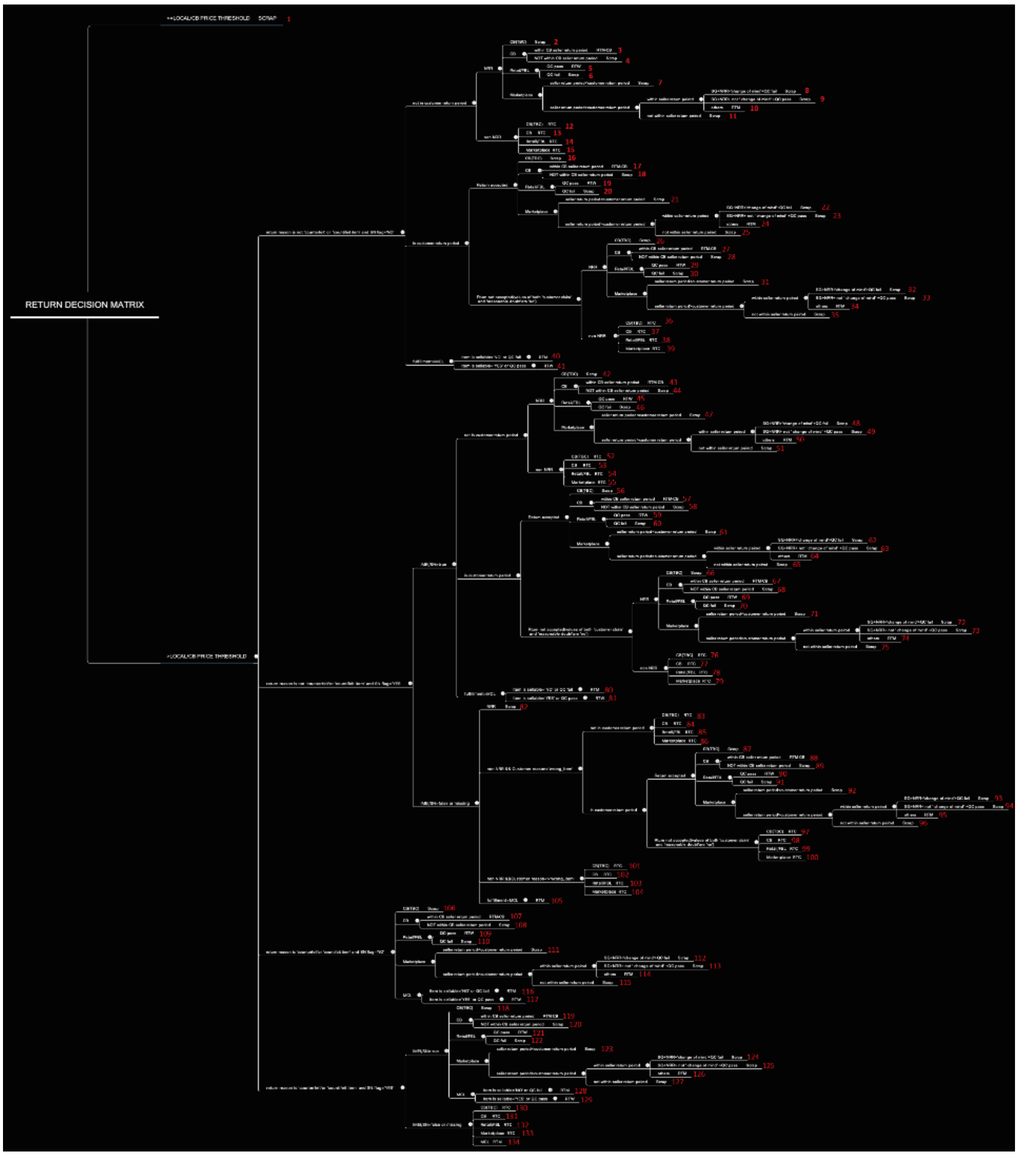
2nd Decision Node: Scrap without Quality Check

After items arrive at the warehouse, they are sent to the Quality Check station and scanned. Items sold through the Marketplace channel with a listed price of less than SGD 14 (1 USD = 1.36 SGD as on April 01, 2022), and items sold through the Cross-Border channel with a listed price of less than SGD 10 are sent directly to Scrap without going through the quality check process. All other items proceed to the quality check process.

3rd Decision Node: Quality Check

At the Quality Check station, returned items are checked against the decision matrix in Figure 12 for their return reasons and product condition. Items are then handled according to the outcome of the decision algorithm. There is an exception for items with outcome “Return to Customer”: they are checked manually by the operator once again to ensure that there is a legitimate reason to return item to customer.

Figure 12: Current Return Decision Matrix for Lazada (Diagram for illustrative purposes)



4th Decision Node: Scrap with Salvage Cost

For items that are sent to Scrap, if the listed product price is above SGD 200, they will be sold to the highest bidding second-hand retail shop, usually at 10-15% of the listed price. For items with listed price below SGD 200, they will be given away at no cost to the winning second-hand retail shop.

4.1.3 Difficulties in current product return operations

Difficulties faced in current operations were also discussed and highlighted in the second interview. Several issues were raised by the QA department with regard to the return decision matrix currently in use.

First, returned items that were decided by the matrix to be sent back to customers had to be manually checked by operator once again to ensure that the decision made was correct. The manual checking was done to prevent customer dissatisfaction from having an item they returned sent back to them. Due to complexity of the existing algorithm, reasons for returns as indicated by customers may not be fully understood by the algorithm and misunderstandings may occur. These misunderstandings may result in returned items getting sent back to customers without getting the issues resolved, incurring customers' displeasure and frustration. The additional check on decision outcome incurs cost and time of valuable manpower resources.

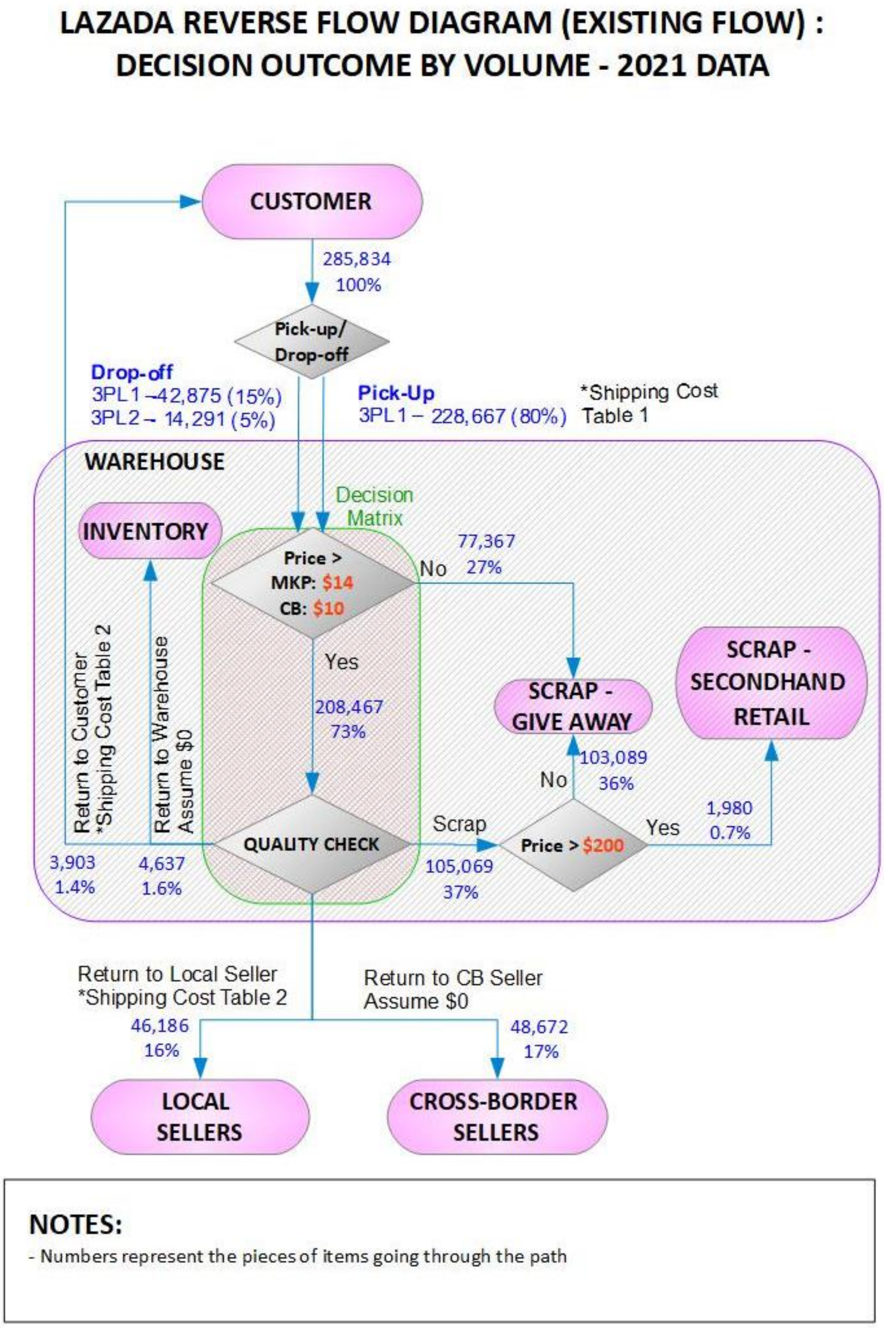
Also, the current decision matrix had lost its efficiency. In today's practice, different departments request the addition of paths in the matrix to meet their individual department requirements or preferences whenever the need arises. These reasons led to a proliferation of paths, with 134 paths created for just 5 decision outcomes. Moreover, the requested algorithm paths from the different departments serve just the individual departments' interests. There was no gatekeeping to evaluate the impact of requests from department, especially in terms of cost. (e.g., the Customer Experience Department could call for algorithm decisions that favor a positive customer experience, even at the cost of company). This practice resulted in a decision algorithm that favors the interests of customers and sellers as seen by the number of paths leading to each decision outcome listed in Table 2. The actual distribution of returns by volume for each decision outcome for the year 2021 is shown along with it. For better visualization, the flow of returns to each decision outcome by volume is also illustrated in the flow diagrams in Figure 13.

Table 2: Paths and distribution of returns for each decision outcome for 2021 data

Decision Outcome	Number of paths	Return Statistics (2021)	
		No. of Returns*	Return Value (SGD)*
Scrap	65	180,839	XXX
Return to Customer	32	4,291	XXX
Return to Cross-Border Seller	9	49,881	XXX
Return to Local Seller	15	46,186	XXX
Return to Warehouse	13	4,637	XXX
Total	134	285,834	XXX

**Numbers are masked or edited to conceal sensitive information*

Figure 13: Process Flow by Volume (2021 data)



**Numbers are masked or edited to conceal sensitive information*

In 65 of the 134 paths, the decision outcome is to have the product sent to "Scrap". This decision contrasts greatly with the number of the rest of the decision outcomes and results in a huge proportion of over 63% of returned items sent to scrap. The problem with the volume of returns is compounded by another issue: the cost of returned items sent to scrap are fully borne by Lazada.

Existing refund practices for Lazada (see Table 3) show a bias towards customers and sellers. The reverse logistics cost is all borne by Lazada regardless of the decision outcome. The forward logistics cost is borne by customer only when the decision outcome for returned item is to "Return to

Customer". Even in the case of returns being sent back to sellers, the forward logistic costs are paid by customer and reverse logistics costs are borne by Lazada. When an item is sent to scrap, all cost related to the item is borne by Lazada. Such lopsided refund policies contribute to the high overall return cost. This arrangement will be examined closer in section 4.2.3.1 for recommended modifications.

Table 3: Cost-bearing Party for Each Decision Outcome

	Forward Logistics Cost	Product Selling Price	Reverse Logistics Cost
Return to Customer	Customer	Customer	Lazada
Return to Local Seller	Lazada/ Seller	Seller	Lazada
Return to Cross-Border Seller	Lazada/ Seller	Seller	Lazada
Return to Warehouse	Lazada/ Seller	Seller	Lazada
Scrap	Lazada	Lazada	Lazada

4.1.4 Insights from the Data received (2021)

Using the 2021 returns data, an analysis of product returns by volume was performed. The total volume of returns was 285,834. Percentage volume of returns was split by their sales channel and respective decision outcome. Table 4 shows that Cross-Border products make up ~74% of the total returns. When compared to the monthly sales percentage through each channel in Figure 10, Cross-Border products were found to have a higher rate of returns as compared to products from the other two sales channels. Also, of all items returned, an astonishing 63% of returned items are scrapped.

Table 4: Product Returns Percentage by Volume for 2021

Channel	Returned to			Scrap	Total
	Customer	Merchant	Warehouse		
CB – FD	0%	0%	0%	1%	1%
Cross-Border	0%	17%	0%	56%	74%
Marketplace	1%	16%	0%	4%	21%
Retail/ FBL	0%	0%	2%	2%	4%
Total	**1%**	**33%**	**2%**	**63%**	**100%**

The same analysis was done for product returns by value, as shown in Table 5. The total value of returns was found to be SGD XXX. The value of products scrapped contributed to a significant percentage of the total returned products value at 40%, totaling SGD XXX. The lower percentage of products scrapped by value compared to volume suggested that most of the scrapped items had value lower than the average.

Table 5: Product Returns Percentage by Value for 2021

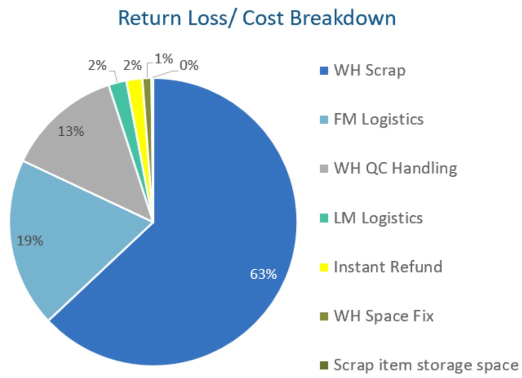
Channel	Returned to			Scrap	Total
	Customer	Merchant	Warehouse		
CB – FD	0%	0%	0%	0%	0%
Cross-Border	1%	20%	0%	28%	49%
Marketplace	3%	29%	0%	7%	38%
Retail/ FBL	2%	0%	5%	6%	13%
Total	**5%**	**49%**	**5%**	**40%**	**100%**

From the value of products scrapped and the return cost breakdown in Figure 2, the first mile logistic cost and quality check handling cost can be calculated. (Note: First mile logistic cost refers to the shipping cost of items from customer to warehouse. Last mile logistics cost refers to the shipping cost of items from warehouse to customer/seller.) Together, they form the 3 major return cost component and are the focus for improving the processes in section 4.2.2.

Table 6: Major Return Cost Component and Amount for 2021

Description	Percentage	Amount (SGD)*
Product Scrap	63%	XXX
First Mile Logistic Cost	19%	XXX
QC Handling	13%	XXX
Last Mile Logistic Cost	2%	XXX
Instant Refund	2%	XXX
Warehouse Space	1%	XXX
Scrap item storage space cost	0%	XXX
Total	**100%**	XXX

**Numbers are masked or edited to conceal sensitive information*



Using the cost calculated in Table 6 and tallying the number of items that went through each process, the average cost per item for each process was deduced (see Table 7).

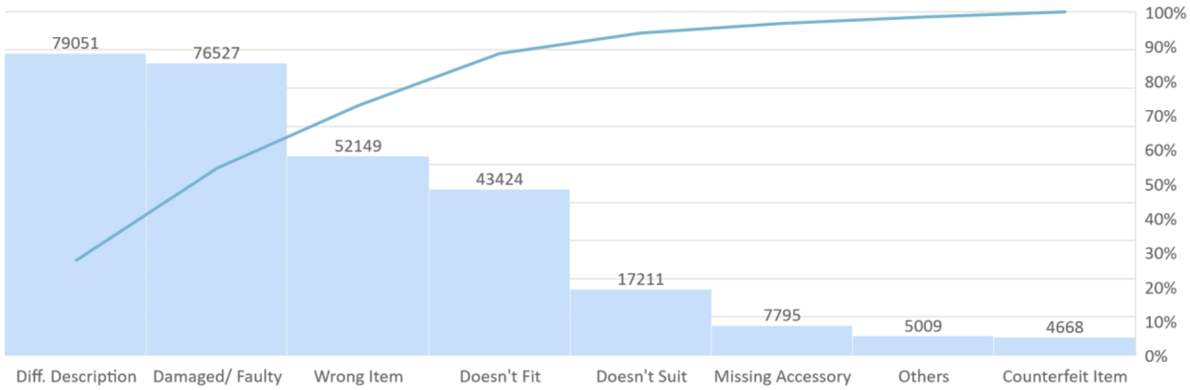
Table 7: Average Cost per Item for Each Process

Description	Percentage	Amount (SGD)**	Items Processed	Avg. Cost/ Unit**
Product Scrap	63%	XXX	180,839	* Listed Price
First Mile Logistic Cost	19%	XXX	285,834	XXX
QC Handling	13%	XXX	258,043	XXX
Last Mile Logistics Cost	2%	XXX	104,995	XXX
Instant Refund	2%	XXX	-	-
Warehouse Space	1%	XXX	-	-
Scrap Item Storage Space Cost	0%	XXX	-	-
Total	100%	XXX	-	-

Note:
**Cost of Product Scrap would be the listed price of the product.*
***Numbers are masked or edited to conceal sensitive information*

Next, product returns volume as per reason quoted by customers for the returns was studied. It was found that over 80% of the returns observed were due to items having different product descriptions, items being damaged, or items being wrongly dispatched to the customer. Figure 14 depicts the details of product returns as per the reasons stated by customer for 2021.

Figure 14: Reasons for Product returns for 2021



Since a major proportion of cost results from products that are scrapped, salvaging the value of these products will be an area of focus. To identify the distribution of products as per their price range, an analysis of 180,839 scrapped products was performed. As per current practise, only items with a listed price above SGD 200 are salvaged with some salvage value. These items made up less than 1% of the total items scrapped. In other words, of all items scrapped, more than 99% had no salvage value. From 2021 returns data, an approximate of 2.5% value of all products scrapped were salvaged. This salvage value is too low and warrants a deeper investigation of alternatives to increase salvage value. Hence, there is a need to reassess price boundaries for defining products with salvage value, and to increase the percentage of salvage value. Table 8 lists the distribution of product return reasons mapped along their price ranges.

Table 8: Price Distribution of Scrapped Products for 2021

Reason	**Percentage of Scrapped products as per Price range (Price in SGD)**						
	0 - 10	**10 - 20**	**20 - 50**	**50 - 100**	**100 - 200**	**200+**	**Total**
Counterfeit Item	1%	0%	0%	0%	0%	0%	1%
Damaged/ Faulty Item	11%	9%	5%	2%	1%	0%	27%
Don't Want/ Doesn't Fit	2%	3%	2%	1%	0%	0%	8%
Don't Want/ Doesn't Suit	1%	1%	1%	1%	0%	0%	5%
Doesn't Match Description	14%	12%	5%	1%	0%	0%	33%
Expired/ Damaged Product	0%	0%	0%	0%	0%	0%	1%
Missing Accessory	1%	1%	1%	0%	0%	0%	3%
Wrong Item	10%	7%	3%	1%	0%	0%	21%
Others	1%	0%	0%	0%	0%	0%	1%
Total	40%	33%	17%	6%	2%	1%	100%

4.2 Building and validating the model

After reviewing the initial results from the data, a model emulating the as-is state of operations was built using Python programming language.

4.2.1 As-Is State Model

The as-is state model was built based on historical data received from Lazada from January to December 2021.

4.2.1.1 Parameters for As-Is State Model

Parameters for each decision nodes as depicted in the current process flow diagram in Figure 12 were identified. The variable type for each parameter is listed in Table 9, along with its availability in the historical data provided by Lazada.

Table 9: Algorithm Parameters for As-Is Model

S. No.	Algorithm Parameters	Variable Type	Available in Provided Returns Data	Input type for As-Is data set
1	Price	Distribution	Yes	As given
2	Return reason - Counterfeit?	Yes/No	Yes	As given
3	Serial Number Available?	Yes/No	Yes	As given (*Retail only)
4	IMEI/Serial Number matched	Yes/No	No	By %
5	QC result	Yes/No	Yes	As given
6	Fulfilment Type	Categorical	Yes	As given
7	In Customer Return Period?	Yes/No	No	By %
8	Is fulfilment type ‘MCL’?	Yes/No	Yes	As given
9	NRR status?	Yes/No	No	By %
10	Within Seller return period?			
a.	*Marketplace*	Yes/No	No	By %
b.	*Cross-border*	Yes/No	No	By %
c.	*Warehouse*	Yes/No	No	By %
11	Seller return period > customer return period?			
a.	*Marketplace*	Yes/No	No	By %
b.	*Cross-border*	Yes/No	No	By %
c.	*Warehouse*	Yes/No	No	By %
12	Is return reason "Change of mind"?	Yes/No	Yes	As given
13	Reasonable doubt?	Yes/No	No	As given
14	Customer Claim	Yes/No	No	As given
15	Is item sellable?	Yes/No	No	As given
16	Is return reason "Wrong item"?	Yes/No	No	As given

The percentage split between each path of the decision nodes was then determined by the percentage in the historical dataset provided. However, information on whether the item was “Within Seller return period?” and “Seller return period> customer return period?” was not available in the historical data provided. For these parameters with no information, values were assumed. These assumed values were manually adjusted, and the cost of returns and quantity of returns were computed repeatedly till their values matched very closely to the ones in the historical data provided earlier. The assumed values were then used as the percentage split.

The parameters and assumptions used to build the as-is model are shown in Table 10:

Table 10: Values of algorithm parameters for As-Is Model

S. No.	Algorithm Parameters	Percentage for Parameter = Yes*	Remarks (Information provided by Lazada)
1	Price		
2	Return reason - Counterfeit?		
3	Serial Number Available?		
4	IMEI/Serial Number matched	XXXX	Not matched: < 10/ month
5	QC result		
6	Fulfilment Type		
7	In Customer Return Period?	XXXX	Not in customer return period: < 3 cases a month (Assume 30000/ month)
8	Is fulfilment type ‘MCL’?		
9	NRR status?	0	Status no longer in use
10	Within Seller return period?		
a.	Marketplace	XXXX	No data
b.	Cross-border	XXXX	No data
c.	Warehouse	XXXX	No data
11	Seller return period > customer return period?		
a.	Marketplace	XXXX	No data
b.	Cross-border	XXXX	No data
c.	Warehouse	XXXX	No data
12	Is return reason "Change of mind"?		Reason "do not want" is change of mind
13	Reasonable doubt?		Not in use
14	Customer Claim		Not in use
15	Is item sellable?		Only applicable for Retail/FBL items. "QC Pass"
16	Is return reason "Wrong item"?		

**Numbers are masked or edited to conceal sensitive information*

4.2.1.2 Data Cleaning

Next, the historical data was checked for any anomalies and for any data entries that were not valid. The following data entries were removed:

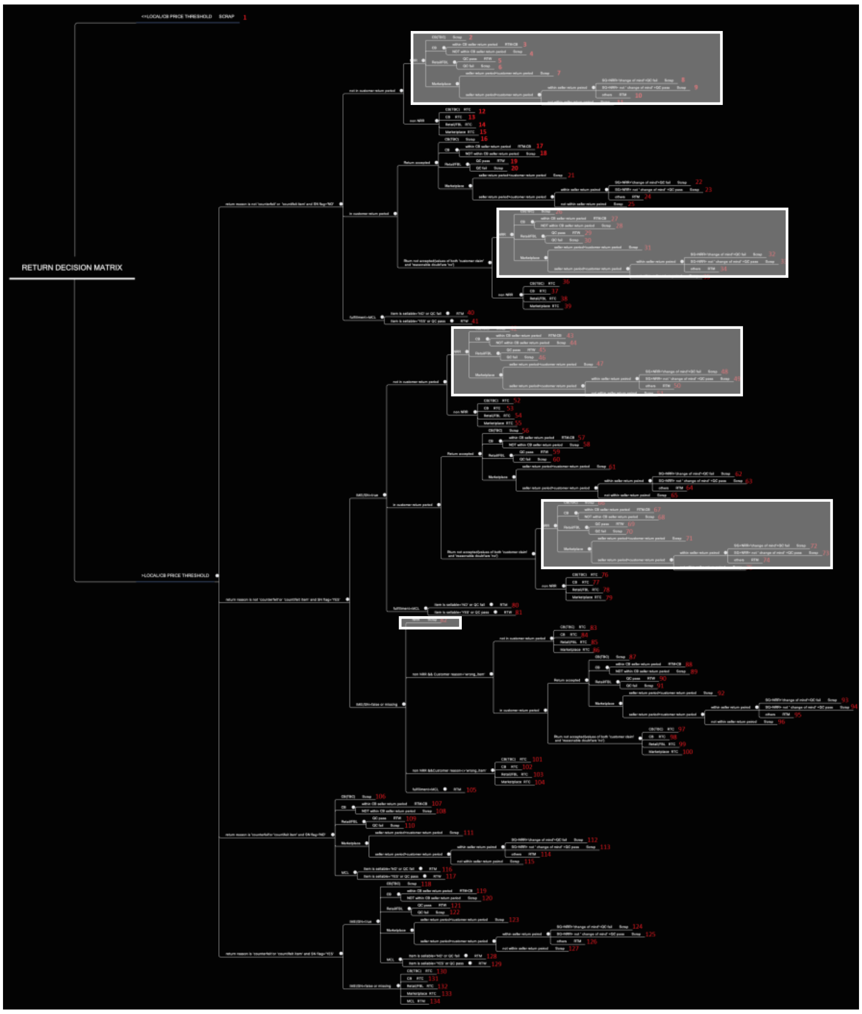
- Data entries with product unit price of 9,999 SGD (used by Lazada as placeholder for free gifts)
- Data entries with product unit price of 0 SGD

Then, the following list of obsolete parameters were identified in the algorithm and removed.

4.2.1.2.1 NRR and non-NRR status

Originally used to earmarked high-value customers by spending amount and hence not reject any return request from these customers, this status is no longer in use. These paths were hence removed. The removed paths are highlighted in silver in Figure 15.

Figure 15: Removal of NRR and non-NRR status from existing algorithm (Diagram for illustrative purposes)



The number of paths after removing the NRR and non-NRR status are shown in Table 11.

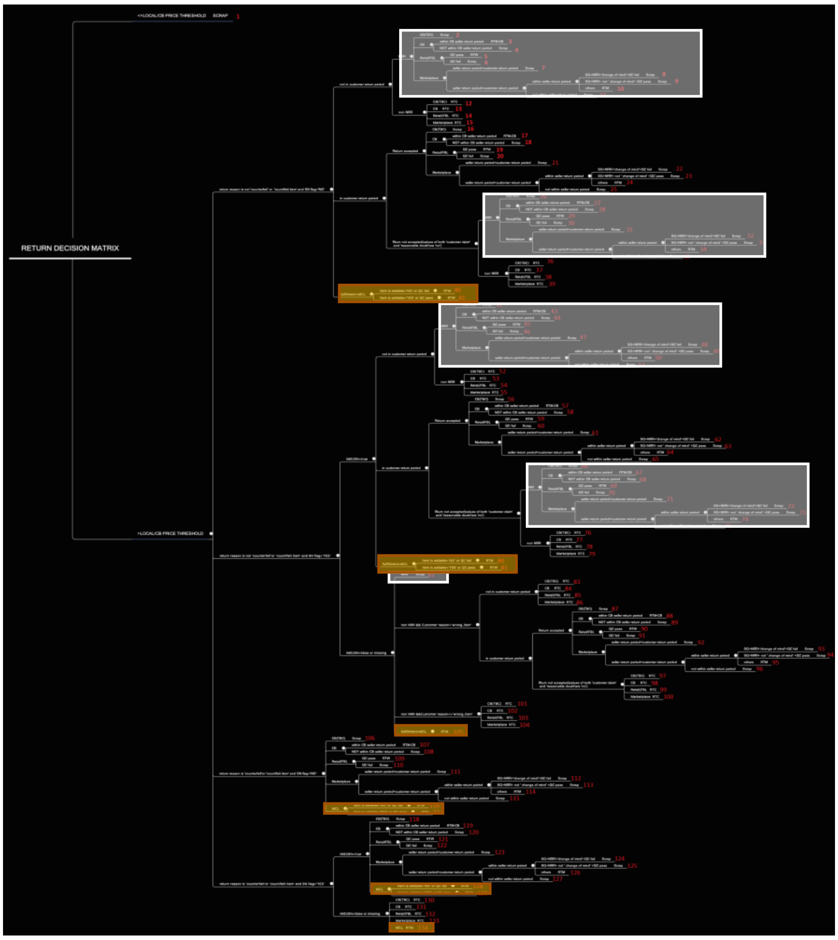
Table 11: Change in number of paths after removing NRR and non-NRR status

Decision Outcome	Number of paths		
	Before Change	Change	After Change
Scrap	65	-29	36
Return to Customer	32	0	32
Return to Cross-Border Seller	9	-4	5
Return to Local Seller	15	-4	11
Return to Warehouse	13	-4	9
Total	134	**-41**	**93**

4.2.1.2.2 MCL Fulfilment Type

A fulfilment type created for test; this parameter is no longer in use. Related paths were hence removed. The removed paths are highlighted in brown in Figure 16.

Figure 16: Removal of MCL fulfilment types from existing algorithm (Diagram for illustrative purposes)



The number of paths after removing the NRR and non-NRR status are shown in Table 12.

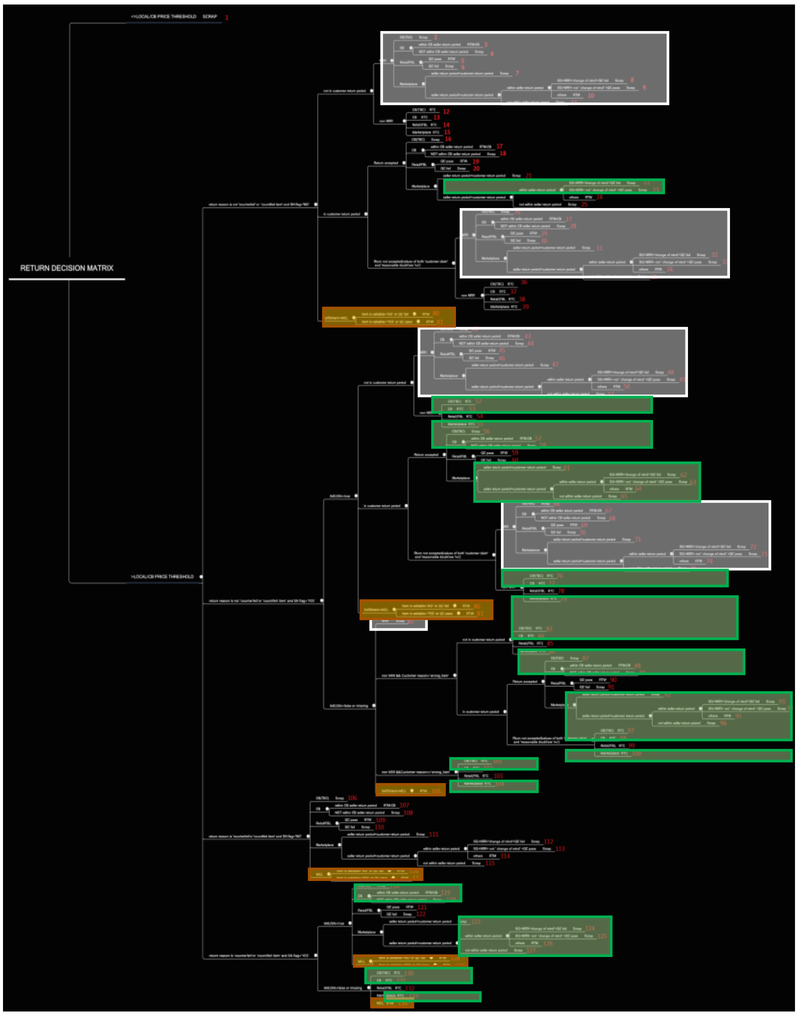
Table 12: Change in number of paths after removing MCL fulfilment type

Decision Outcome	Number of paths		
	Before Change	Change	After Change
Scrap	36	0	36
Return to Customer	32	0	32
Return to Cross-Border Seller	5	0	5
Return to Local Seller	11	-6	5
Return to Warehouse	9	-4	5
Total	**93**	**-10**	**83**

4.2.1.2.3 SN flag for non-retail items

After confirming with Lazada that the parameter of SN flag is used only for items fulfilled by retail/fbl, several paths were found to be irrelevant. Items fulfilled by other channels do not have a SN flag indicator; hence, this parameter was not required for them. These paths are highlighted in green in Figure 17.

Figure 17: Removal of SN flag for non-retail items (Diagram for illustrative purposes)



The number of paths after removing the SN flag for non-retail items are shown in Table 13.

Table 13: Change in number of paths after removing SN flag for non-retail items

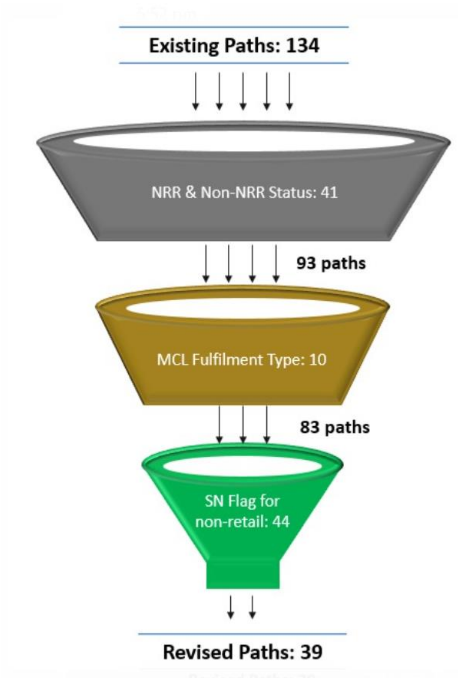
Decision Outcome	Number of paths		
	Before Change	Change	After Change
Scrap	36	-20	16
Return to Customer	32	-18	14
Return to Cross-Border Seller	5	-3	2
Return to Local Seller	5	-3	2
Return to Warehouse	5	0	5
Total	**83**	**-44**	**39**

After the revision to paths in section 4.2.1.2, the consolidated change in number of paths is shown in Table 14 and depicted in Figure 18.

Table 14: Consolidated change in number of paths after removing obsolete parameters

Decision Outcome	Existing Algorithm		After Preliminary Change	
	No. of Paths	%	No. of Paths	%
Scrap	65	49%	16	41%
Return to Customer	32	24%	14	36%
Return to Cross-Border Seller	9	7%	2	5%
Return to Local Seller	15	11%	2	5%
Return to Warehouse	13	10%	5	13%
Total	**134**	**100%**	**39**	**100%**

Figure 18: Depiction of the reduction in paths



The total number of paths was reduced by 71% by removing paths with obsolete parameters. The percentage of items sent to scrap was reduced by 8%. The revised algorithm in Python programming language with the obsolete paths removed is in Appendix G.

4.2.1.3 Total Cost Calculation

Total cost of returns was calculated for each simulation run with a given dataset. The parameters used to calculate the total cost of returns are described below.

4.2.1.3.1 Shipping Cost

While shipping cost is in reality determined by the gross weight of parcel listed in Appendix A, an average cost was used for the shipping cost from customer to warehouse, $Shipping\ Cost_{CW}$, and the shipping cost from warehouse to seller, $Shipping\ Cost_{ws}$. This is because the dataset of returned items provided by Lazada did not include information on weight of parcels.

An updated version of the financial information related to handling product returns was provided by Lazada in Appendix E and the updated shipping costs were calculated from the average of previous months cost.

The shipping cost from customer to warehouse, $Shipping\ Cost_{CW} = XXX\ SGD$. This is also the known as the first mile logistics cost in this project.

The shipping cost from warehouse to seller or customer, $Shipping\ Cost_{ws} = XXX\ SGD$. This is also the known as the last mile logistics cost in this project.

4.2.1.3.2 Quality Check Cost

As understood from Lazada, the cost of quality check (QC) is charged per item; hence the size and time taken for each product would not be required. Cost of quality check, $Cost_{QC}$, for each item inspected can also be determined from the Appendix E.

The cost of quality check, $Cost_{QC} = XXX\ SGD$.

4.2.1.3.3 "No QC" threshold

Price threshold to determine if quality check process is needed will also be reviewed. This price threshold shall be termed "No QC" threshold. Current "No QC" threshold is set as SGD 10 for Cross-Border products, SGD 14 for Marketplace products and none for Retail products.

An optimal range of "No QC" threshold will be determined from a sensitivity analysis and its actual value can be decided from company policy, customer profiling or other alternatives.

4.2.1.3.4 Salvage Value

Salvage value from scrapped products is currently determined to be 20% for products with listed price above SGD 200, and none for products below. The price boundary of SGD 200 was determined by second-hand retail vendors who are only interested to purchase items with listed price above that.

The impact of changing the salvage value and the price boundary of salvage value is determined in a sensitivity analysis in the later part of the report.

4.2.1.3.5 Refund to Customer

While refund to customer was initially determined in Equation 1, data on the discount and forward shipping cost is not made available for the project. There is also a complex range of criteria for determining the discount and forward shipping cost to be charged. In addition, the cost difference after deducting the discount and adding the shipping cost is not expected to differ significantly from the product listed price. Hence, this project will not consider the discount and forward shipping cost in calculation of refund to customer. For this project, Equation 4 will be used to calculate refund to customer.

$$Refund\ to\ Customer\ = Product\ Listed\ Price \tag{4}$$

4.2.1.3.6 Refund from Seller

While refund from seller was initially determined in Equation 2, data on the discount offered and forward shipping cost is not made available for the project. The cost calculated from Equation 2 is also not expected to be significantly different from the product listed price, especially for products with higher values. The low volume of items returned to seller (34% of total returned items) also limits the impact of this cost difference on the total cost of returns. Hence, to simplify the model, this project will not consider the discount and forward shipping cost in calculation of refund from seller. For this project, Equation 5 will be used to calculate refund from seller.

$$Refund\ from\ Seller\ = Product\ Listed\ Price \tag{5}$$

4.2.1.3.7 Total Cost of Returns

Cost parameters used in the model to calculate total cost of returns is tabulated in Table 15.

Table 15: Updated Cost Parameters

Parameters	First Mile* $(Shipping\ Cost_{CW})$	Quality Check*	Last Mile* $(Shipping\ Cost_{ws})$
Cost (SGD)	XXX	XXX	XXX

**Numbers are masked or edited to conceal sensitive information*

With the revisions and new added parameters, an updated table for cost of returns for each returned item is listed in Table 16 according to its respective decision outcome. The cost of returns will be calculated by summing each cost component.

Table 16: Cost of Return for each decision outcome

Decision Outcome	Shipping Cost from Customer to Warehouse	Cost of quality check	Shipping cost from Warehouse to Seller	Refund to Customer	Refund from Seller	Product Salvage Value
Sent to Scrap with no quality check (Price < SGD 14 for Marketplace items, Price < SGD 10 for Cross-Border items)	$Shipping\ Cost_{CW}$	-	-	$Product\ Listed\ Price$	-	-
Sent to Scrap (Price >= SGD 200)	$Shipping\ Cost_{CW}$	$Cost_{QC}$	-	$Product\ Listed\ Price$	-	$-(Product\ Listed\ Price\ X\ 10\%)$
Sent to Scrap (Price < SGD 200)	$Shipping\ Cost_{CW}$	$Cost_{QC}$	-	$Product\ Listed\ Price$	-	-
Return to Customer	$Shipping\ Cost_{CW}$	$Cost_{QC}$	$Shipping\ Cost_{WS}$	-	-	-
Return to Cross-Border Seller	$Shipping\ Cost_{CW}$	$Cost_{QC}$	-*	$Product\ Listed\ Price$	$-(Product\ Listed\ Price)$	-
Return to Local Seller	$Shipping\ Cost_{CW}$	$Cost_{QC}$	$Shipping\ Cost_{WS}$	$Product\ Listed\ Price$	$-(Product\ Listed\ Price)$	-
Return to Warehouse	$Shipping\ Cost_{CW}$	$Cost_{QC}$	-	$Product\ Listed\ Price$	$-(Product\ Listed\ Price)$	-

Note:
**There is no shipping cost from warehouse to Cross-Border seller as this cost is not under the purview of the QA department and will not be included into the calculation of cost of returns.*

4.2.1.4 <u>Results from historical data</u>

With the data preparation and total returns cost calculation completed, an algorithm for making returns decision outcome was written in the Python programming language. The algorithm can be found in Appendix G. A comparison of actual data and simulated data was done using September-2021 and October-2021 data as they were given before the rest of the dataset. The calculated returns cost and quantity in each outcome was compared against the actual data provided by Lazada (see Table 17). Variation between the calculated cost is kept below 3%, and variation between the quantity for each decision outcome is mostly kept below 4%. The only exception would be the quantity of items returned to customer. Since the quantity is low for that category, a small variation would appear as a high percentage. Overall, the low variation proves that the algorithm and parameters used in the model are accurate.

Table 17: Comparison between actual data and simulated data for Sep and Oct 2021

Description	Split	Amount (SGD)		Variation
		Actual**	Simulated**	
Product Scrap	63%	XXX	XXX	1.68%
First Mile Logistic Cost	19%	XXX	XXX	-0.10%
QC Handling	13%	XXX	XXX	-0.08%
Last Mile Logistic Cost	2%	XXX	XXX	3.26%
Instant Refund	2%	XXX	XXX	
Warehouse Space	1%	XXX	XXX	
Scrap item storage space cost	0%	XXX	XXX	
Total	**100%**	XXX	XXX	**1.16%**

**Assumptions in the cost calculation:*

- *Cost of "Instant Refund" assumed to be the same as the cost of "Last Mile Logistic Cost"*
- *Cost of "Warehouse Space" assumed to be the same every month*

***Numbers are masked or edited to conceal sensitive information*

Decision Outcome	Split	Quantity		Variation
		Actual	Simulated	
Sent to Scrap	67%	35,928	35,522	-1.13%
Return – Customer	0.1%	55	46	-16.36%
Return to Cross-Border Seller	16%	8,644	8,808	1.90%
Return to Local Seller	15%	8,194	8,461	3.26%
Return to Warehouse	1.2%	674	658	-2.37%
Total	**100%**	**53,495**	**53,495**	

4.2.1.5 <u>Parameters for generated dataset</u>

With the decision algorithm created, the team needed to create a method to generate a dataset for running simulations. The parameters of the historical dataset received from Lazada were characterized as shown in Table 18.

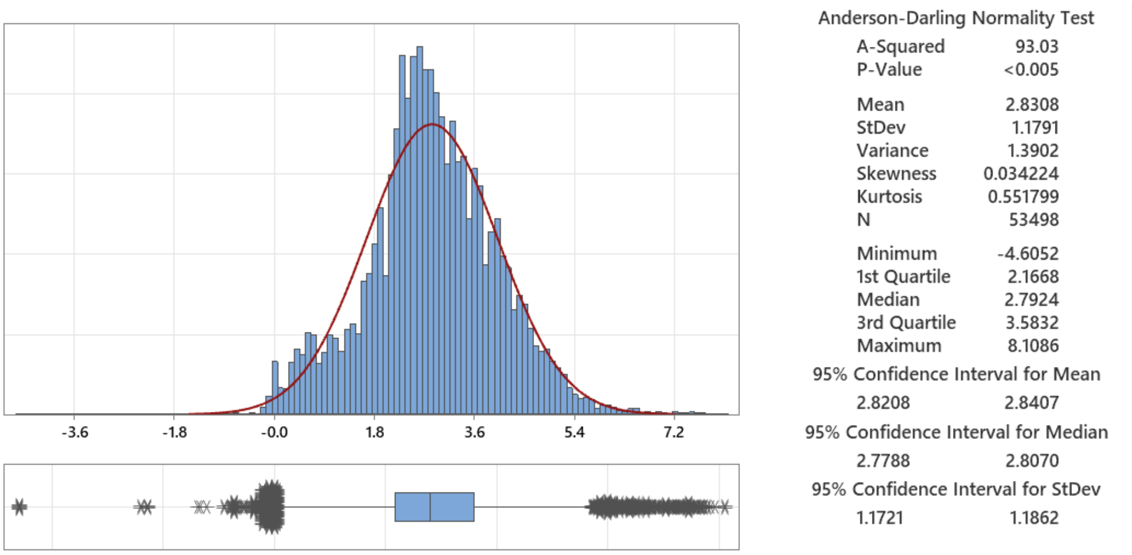
Table 18: Parameters for generating dataset

S. No.	Algorithm Parameters	Variable Type	Input type As-Is	Percentage of Distribution/ Percentage for Parameter = Yes*
1	Price	Probability	Probability	Lognormal Mean = 2.83, S.D. = 1.18
2	Return reason - Counterfeit?	Yes/No	By %	XXX
3	Serial Number Available?	Yes/No	By %	XXX
4	IMEI/Serial Number matched	Yes/No	By %	XXX
5	QC result	Yes/No	By %	XXX
6	Fulfilment Type			
a.	*Marketplace*			XXX
b.	*Cross-border*	Categorical	By %	XXX
c.	*Warehouse*			XXX
7	In Customer Return Period?	Yes/No	By %	XXX
8	Is fulfilment type 'MCL'?	Yes/No	By %	0
9	NRR status?	Yes/No	By %	0
10	Within Seller return period?			
a.	*Marketplace*			XXX
b.	*Cross-border*		By %	XXX
c.	*Warehouse*			XXX
11	Seller return period > customer return period?			
a.	*Marketplace*			XXX
b.	*Cross-border*	Yes/No	By %	XXX
c.	*Warehouse*			XXX
12	Is return reason "Change of mind"?	Yes/No	By%	XXX
13	Reasonable doubt?	Yes/No	By%	0
14	Customer Claim	Yes/No	By%	0
15	Is item sellable?	Yes/No	By%	XXX
16	Is return reason "Wrong item"?	Yes/No	By%	XXX

**Numbers are masked or edited to conceal sensitive information*

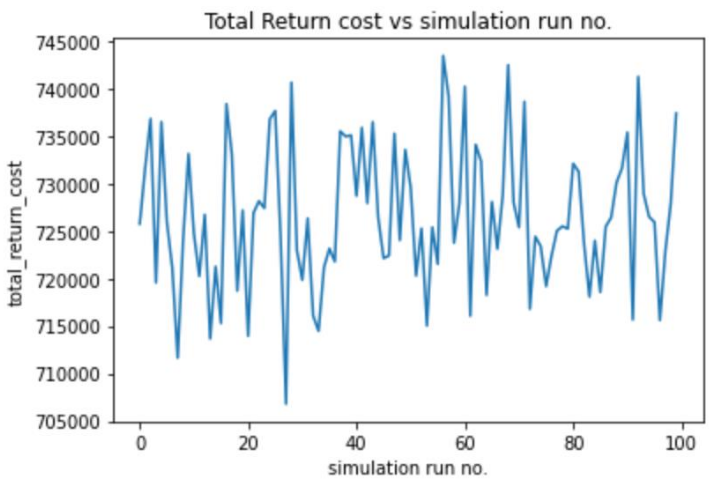
The price distribution was found to follow a lognormal distribution in Figure 19. Using the Anderson-Darling Normality Test, when the logarithm of prices is tested against a normal distribution mean of 2.83 and standard deviation of 1.18, the p-value was found to be less than 0.05. The mean and standard deviation also falls between their respective 95% confidence interval. This means that the lognormal distribution used is highly representative of the actual price distribution, with a confidence of 95%.

Figure 19: Lognormal price distribution



Using the parameters in Table 18, an initial simulation was done with 100 runs of 30,000 dataset in each run. 30,000 datasets in each run were chosen as the average number of return items per month. A plot of the total return cost for each run is shown in Figure 20 with the maximum, minimum and standard deviation calculated for each simulation. It can be observed that there is a standard deviation of about 1% in the total cost calculated. Further fine-tuning can be done to decrease the standard deviation for the generated dataset.

Figure 20: Plot of initial total return cost for generated dataset



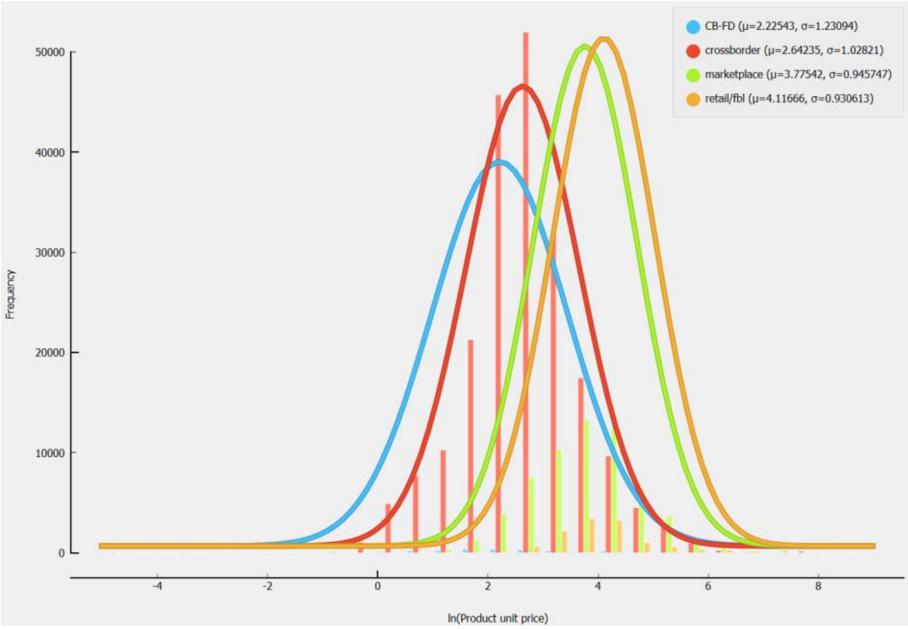

```
Average total return cost:  726592.9798790936
Standard deviation of total return cost:  7601.43686594548
Maximum total return cost:  743452.6071859333
Minimum total return cost:  706786.9852464965
```

4.2.1.6 <u>Fine-tuning of generated dataset</u>

To identify opportunities for fine-tuning of the model, algorithm parameters in Table 18 was segmented by fulfilment channels and analyzed. *(Note: Products fulfilled by CB-FD are considered to be crossborder products.)*

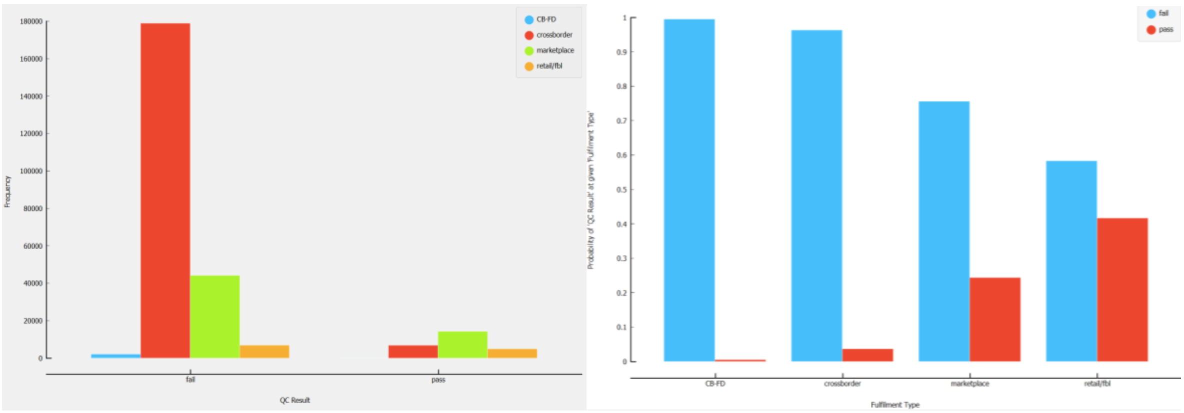
The lognormal of product unit price was found to vary widely across different fulfilment channels in Figure 21.

Figure 21: Product Unit Price by Fulfilment Channel



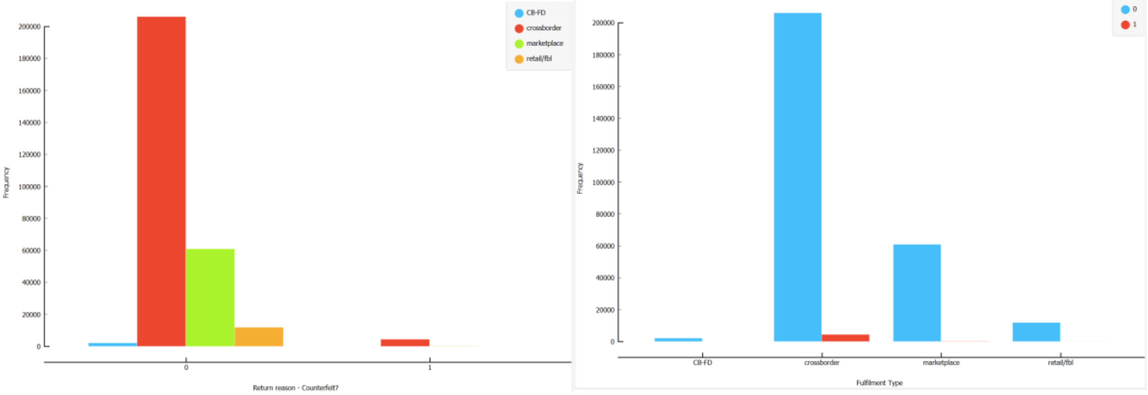
Segmenting by channel also revealed that Quality Check (QC) results vary widely across the different fulfilment channels as seen in Figure 22. The passing rate of QC result is much higher for items fulfilled by retail/fbl, followed by marketplace items, whereas crossborder products has the lowest passing rate.

Figure 22: Quality Check Results by Fulfilment Channels



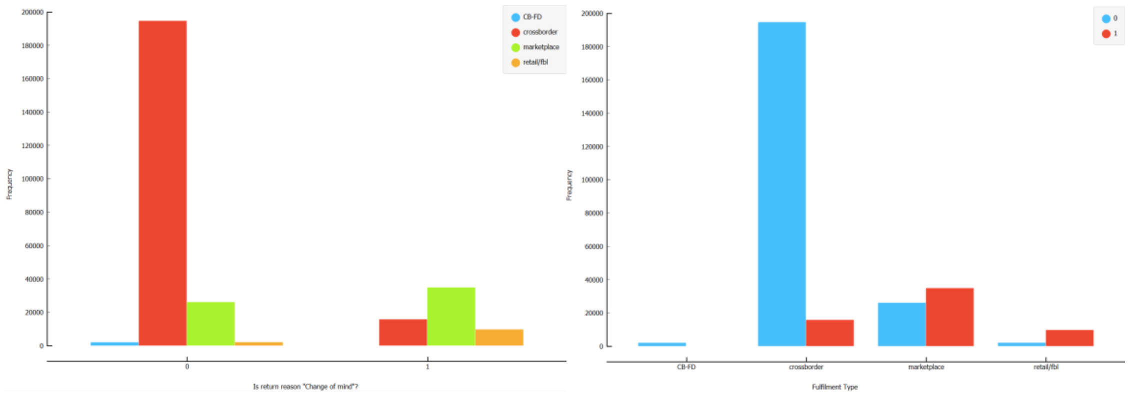
From Figure 23, it can be seen that counterfeit items were found to occur most commonly among crossborder products and rarely in items of other fulfilment channels.

Figure 23: Counterfeit by Fulfilment Channels



From Figure 24, items fulfilled through the marketplace or retail/fbl channels are more likely to be returned due to a return reason of “Change of Mind” than other fulfilment types. In fact, “Change of Mind” account for more than half of returned items from these 2 channels.

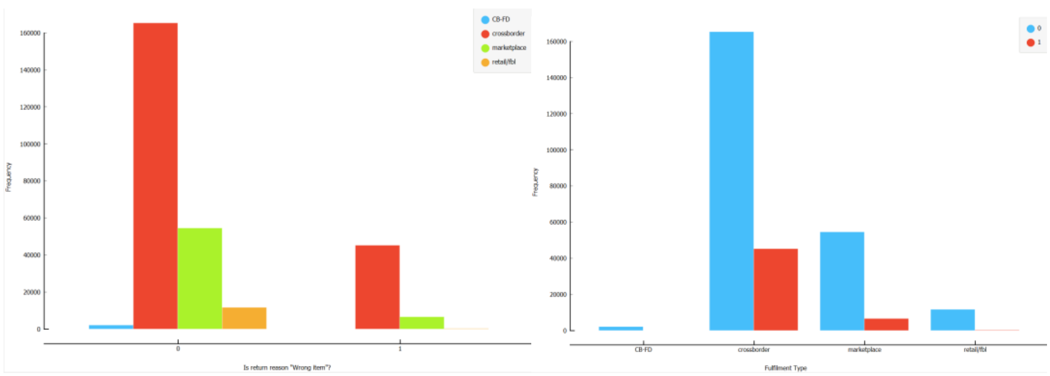
Figure 24: "Change of Mind" items by Fulfilment Channels



Crossborder products were found to be most likely returned due to return reason of “Wrong item” than other fulfilment types.

Figure 25 shows the percentage split of items returned due to “Wrong item” for each of the fulfilment types.

Figure 25: "Wrong item" by Fulfilment Channels



After identifying the above algorithm parameters by segmentation, the results are tabulated in Table 19.

Table 19: Algorithm Parameters by Fulfilment Channels

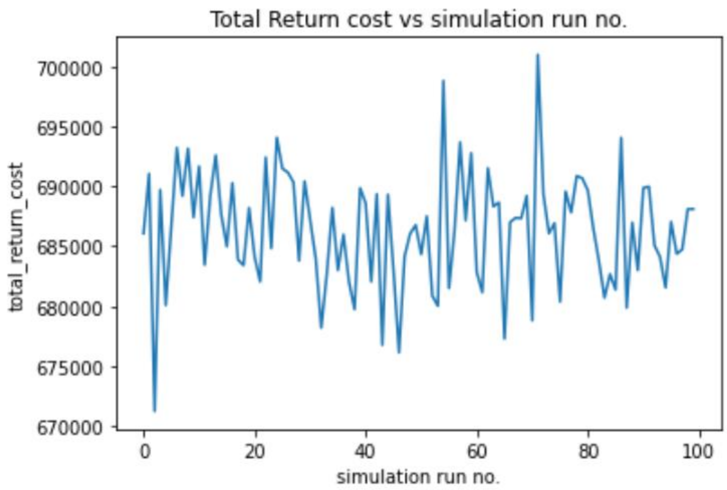
Algorithm Parameters			
Lognormal Price Distribution	Fulfilment Channel	Mean	Std Dev.
	CB-FD	2.22543	1.23094
	Crossborder	2.64235	1.02821
	Marketplace	3.77542	0.945747
	Retail/fbl	4.11666	0.930613
QC Result	Fulfilment Channel	Fail	Pass
	CB-FD	XXX	XXX
	Crossborder	XXX	XXX
	Marketplace	XXX	XXX
	Retail/fbl	XXX	XXX
Counterfeit	Fulfilment Channel	0	1
	CB-FD	XXX	XXX
	Crossborder	XXX	XXX
	Marketplace	XXX	XXX
	Retail/fbl	XXX	XXX
"Change of Mind"	Fulfilment Channel	0	1
	CB-FD	XXX	XXX
	Crossborder	XXX	XXX
	Marketplace	XXX	XXX
	Retail/fbl	XXX	XXX
"Wrong item"	Fulfilment Channel	0	1
	CB-FD	XXX	XXX
	Crossborder	XXX	XXX
	Marketplace	XXX	XXX
	Retail/fbl	XXX	XXX

**Numbers are masked or edited to conceal sensitive information*

4.2.2 Baseline Scenario

The algorithm parameter by fulfilment channels in Table 19 was then ready to be incorporated into the as-is model built to reduce variability. Using the parameters in Table 18 and Table 19, the fine-tuned simulation was done with similarly 100 runs of 30,000 dataset in each run. The result with a plot of the total return cost for each run is shown in Figure 26 with the maximum, minimum and standard deviation calculated for each simulation. The standard deviation is observed to decrease to 0.7% as compared to 1% in Figure 20.

Figure 26: Plot of total returns cost for the Finetuned Simulation Result (0.7% standard deviation)




```
Average total return cost:  686377.9976498648
Standard deviation of total return cost:  4815.812101384168
Maximum total return cost:  700983.1787138989
Minimum total return cost:  671242.7514037071
```

4.2.2.1 Results

This fine-tuned as-is model was used as the baseline scenario for comparison of results with alternative scenarios.

Table 20: Baseline Scenario Results

No. of products in each run	No. of simulation runs	Algorithm	Average Total Cost (SGD)
30,000	100	Baseline	686,378

4.2.3 Developing Alternative Scenarios

Since product scrap, first mile logistics, and quality check handling cost contribute to 95% of the total returns cost, our focus was on these components when developing the alternative scenarios.

4.2.3.1 Scenario 1: Existing Algorithm Review and Revision

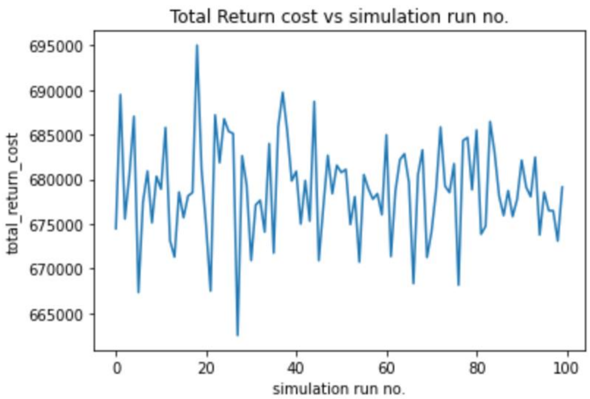
The existing algorithm was first reviewed and revised to ensure its logicality. As mentioned in section 4.1.3, the current algorithm is a compilation of request from various departments and may not represent the best interest of the company. Hence each path in the existing algorithm was re-examined for its logicality and appropriate outcome.

The following amendments were made to the algorithm:

a. Items that are within the local seller's return period will be returned to local seller regardless of condition.
b. Items labelled "Counterfeit" and without Serial Number (SN) will be returned to local seller regardless of return period

The results of running the simulation for Scenario 1 are plotted in Figure 27. There is an expected savings of approximately 1% in cost after implementation.

Figure 27: Plot of total returns cost for Scenario 1



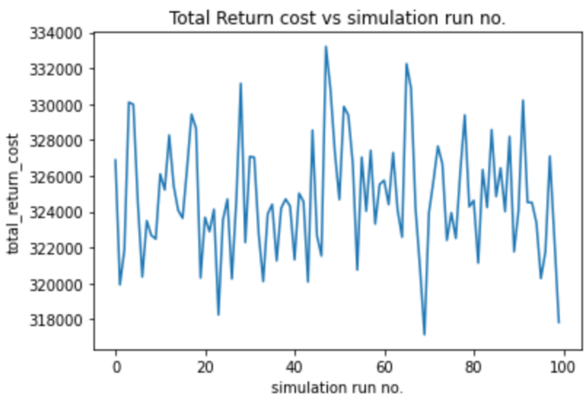

```
Average total return cost:  678891.6487667985
Standard deviation of total return cost:  5458.325074083183
Maximum total return cost:  695024.2379123326
Minimum total return cost:  662527.0385933509
```

4.2.3.2 Scenario 2: Pegging of Seller's Return Period to Customer's Return Period

An alternative scenario developed was to test the impact on total return cost when seller's return period is pegged to customer's return period. This means that the seller's return period is determined by Lazada to be the same as customer's return period, and if an item is within customer's return period, it will be within the seller's return period.

The total cost of returns for Scenario 2 is shown in Figure 28 and a significant savings of 53% is observed.

Figure 28: Plot of total returns cost for Scenario 2



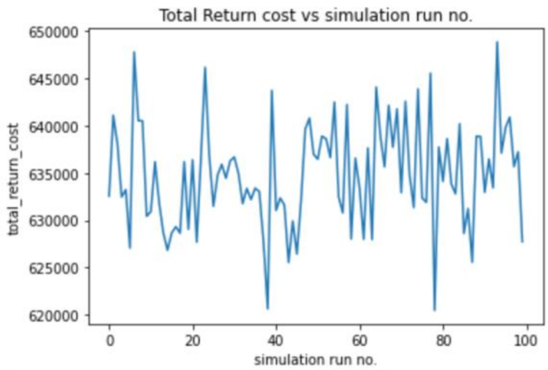

```
Average total return cost:  324777.80733672134
Standard deviation of total return cost:  3205.2920137389183
Maximum total return cost:  333212.7526451907
Minimum total return cost:  317146.8894313566
```

4.2.3.3 Scenario 2a: Pegging of Local Seller's Return Period to Customer's Return Period

The results from Scenario 2 in section 4.2.3.2 show a great impact. Hence, Lazada requested us to delve deeper into the potential of this scenario by applying Scenario 2 only on marketplace products, which is easier to be done in terms of operations as compared to crossborder products. Hence Scenario 2a was developed, where only the local seller's return period is pegged to customer's return period.

The savings for the total cost of returns for Scenario 2a in Figure 29 is found to be significantly less than Scenario 2 at only 7.6%.

Figure 29: Plot of total returns cost for Scenario 2a



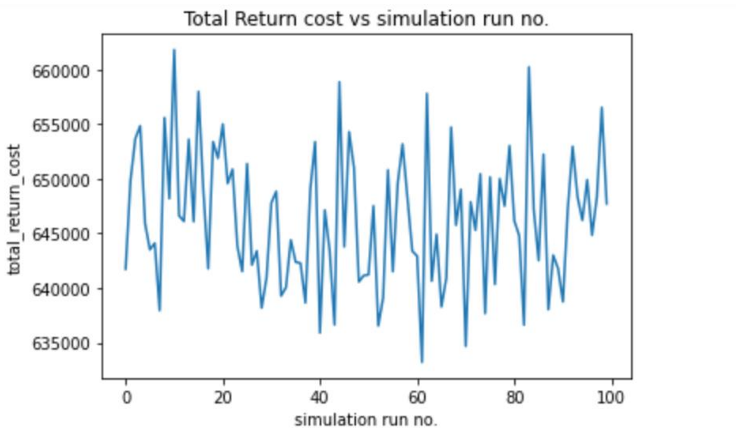

```
Average total return cost:  634771.2637847444
Standard deviation of total return cost:  5543.641687985919
Maximum total return cost:  648845.8435272104
Minimum total return cost:  620481.8469275528
```

4.2.3.4 Scenario 3: Addition of "No Collection" Decision Outcome for items to be refunded without collection

To reduce the cost of first mile logistics, an alternative scenario was developed where items which are determined to not go through the Quality Check process and will be scrapped are not collected from customer to warehouse at all. This means that all items directed to path 1 in the current algorithm will not be collected. This will reduce the total First Mile Logistics cost.

A savings of approximately 6% from the total cost of returns was generated, as shown in Figure 30.

Figure 30: Plot of total returns cost for Scenario 3

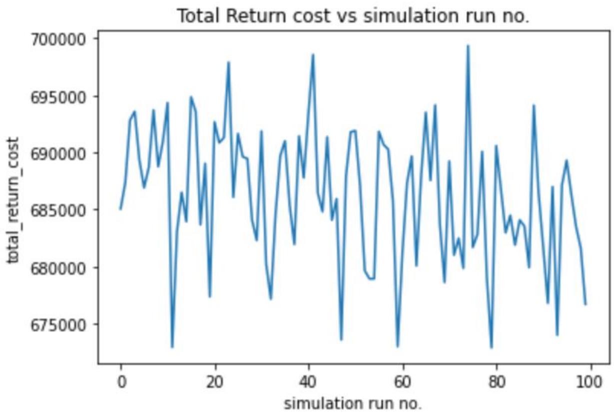



```
Average total return cost:  646287.7777157903
Standard deviation of total return cost:  6120.6652087765215
Maximum total return cost:  661813.418796204
Minimum total return cost:  633210.9040015806
```

4.2.3.5 Scenario 4: Mandatory "Return to Merchant" instead of "Scrap" for all product with listed price above 200 SGD

An alternative scenario requested by Lazada, Scenario 4 will identify all products above 200 SGD that have a decision outcome of "Scrap" and change it to "Return to Merchant" instead. This will apply to products of all fulfilment types.

Figure 31: Plot of total returns cost for Scenario 4



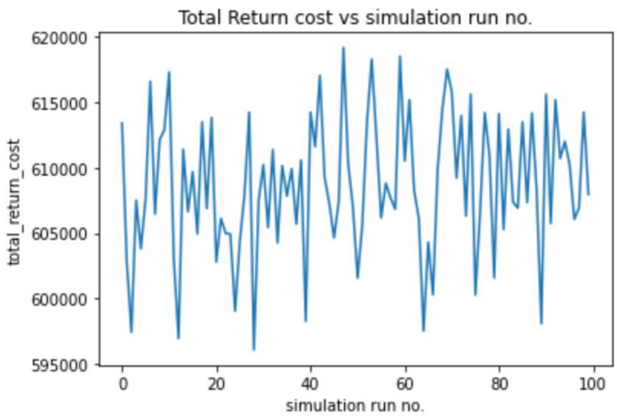

```
Average total return cost:  686207.2322692572
Standard deviation of total return cost:  5844.21456420504
Maximum total return cost:  699337.2246391872
Minimum total return cost:  672907.8114465048
```

4.2.3.6 Scenario 5: Combination of Scenario 1, 2a, 4

After a discussion with Lazada on the results from the earlier scenarios, an alternative scenario 5 was decided. Scenario 5 combines Scenarios 1, 2a and 4 to determine the compounded savings from implementing these scenarios. *(Note: Scenario 2a was chosen over Scenario 2 as Lazada determined that it would be more feasible to carry out Scenario 2a instead of Scenario 2.)*

A total savings of 11% can be realized with the combination of Scenario 1, 2a and 4 as shown in Figure 32.

Figure 32: Plot of total cost returns for Scenario 5




```
Average total return cost:  608645.77322976
Standard deviation of total return cost:  5259.499751230549
Maximum total return cost:  619168.0590736457
Minimum total return cost:  596082.1064965731
```

4.2.3.7 Results

Results of the above scenarios are tabulated in Table 21.

Table 21: Tabulated total cost of returns for all scenarios

No. of products in each simulation run	No. of simulation runs	Algorithm	Average Total Returns Cost	% of Baseline Scenario
30,000	100	Baseline Scenario	686,378	100%
30,000	100	Scenario 1	678,891	98.9%
30,000	100	Scenario 2	324,778	47.3%
30,000	100	Scenario 2a	634,771	92.4%
30,000	100	Scenario 3	646,288	94.1%
30,000	100	Scenario 4	650,538	94.7%
30,000	100	Scenario 5	608,645	88.6%

The historical returns dataset for September and October 2021 was also ran through all the scenarios and have its percentage of savings compared to the ones obtained from the generated dataset in Table 21. Difference in savings percentage was observed to be relatively small below 3% for all scenarios except scenario 2 with 5.4%. Hence the percentage of savings was reaffirmed, and the generated dataset was once again proven to follow closely to the actual dataset.

Table 22: Comparison of scenarios saving percentage for historical and generated dataset

Algorithm	Historical Dataset (Sep-Oct 21)		Generated Dataset		Diff. in savings %
	Average Total Returns Cost	% of Baseline Scenario	Avg. Total Returns Cost	% of Baseline Scenario	
Baseline	1,195,780	100.0%	686,378	100.0%	-
S1	1,175,607	98.3%	678,891	98.9%	-0.6%
S2	630,322	52.7%	324,778	47.3%	5.4%
S2a	1,134,342	94.9%	634,771	92.4%	2.4%
S3	1,125,660	94.1%	646,288	94.1%	0.0%
S4	1,103,266	92.3%	650,538	94.7%	-2.5%
S5	1,041,930	87.1%	608,645	88.6%	-1.5%

4.3 Sensitivity Analysis

After obtaining results from section 4.2, sensitivity analysis was performed on selected parameters to observe how changing it impacts the total return cost.

4.3.1 "No QC" Threshold

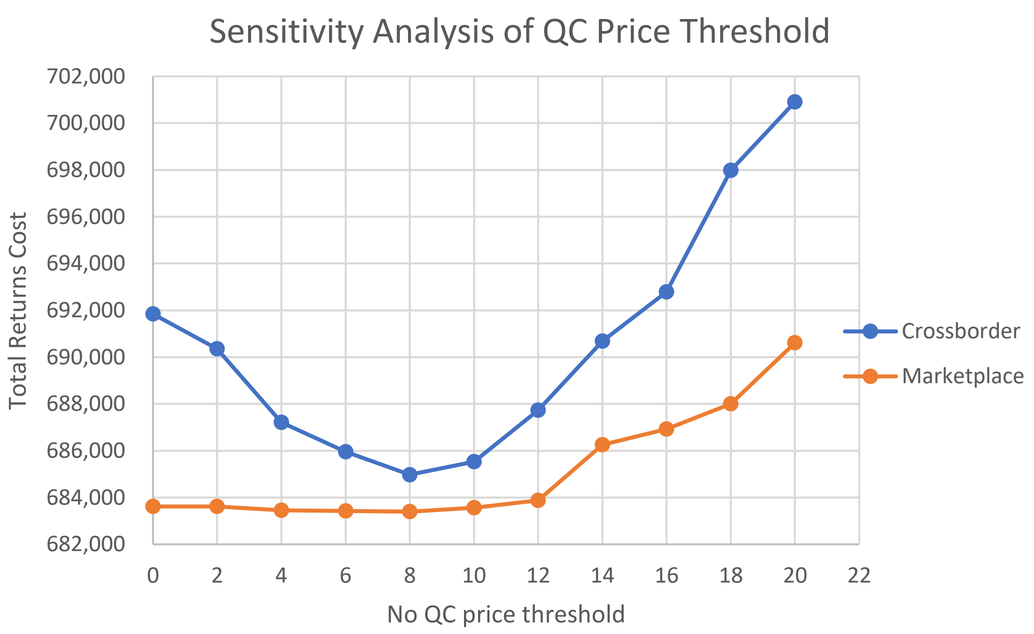
As the first decision node in the decision outcome matrix, changing the "No QC" price threshold was done separately for both marketplace and crossborder items.

The sensitivity analysis was performed using the baseline scenario and results were tabulated in Table 23 and plotted in Figure 33.

Table 23: Sensitivity Analysis of "No QC" Price Threshold

Scenario		Crossborder Products		Marketplace Products	
	'No QC Price threshold'	Total Returns Cost	% of total returns cost of baseline	Total Returns Cost	% of total returns cost of baseline
Baseline	0	691,843	100.00%	686,378	100.0%
Baseline	2	690,362	99.79%	684,388	100.1%
Baseline	4	687,209	99.33%	683,099	99.9%
Baseline	6	685,957	99.15%	683,425	100.0%
Baseline	8	684,978	99.01%	683398	100.0%
Baseline	10	685,531	99.09%	683,564	100.0%
Baseline	12	687,735	99.41%	683,884	100.0%
Baseline	14	690,688	99.83%	686,251	100.4%
Baseline	16	692,792	100.14%	686,923	100.5%
Baseline	18	697,985	100.89%	688,008	100.6%
Baseline	20	700,909	101.31%	690,611	101.0%

Figure 33: Sensitivity Analysis of "No QC" Price Threshold



From the graph, the optimal "No QC" price threshold for products fulfilled by marketplace channel would be anywhere between 0 to 12 SGD. The optimal price threshold for products fulfilled by crossborder channel would be 8 SGD.

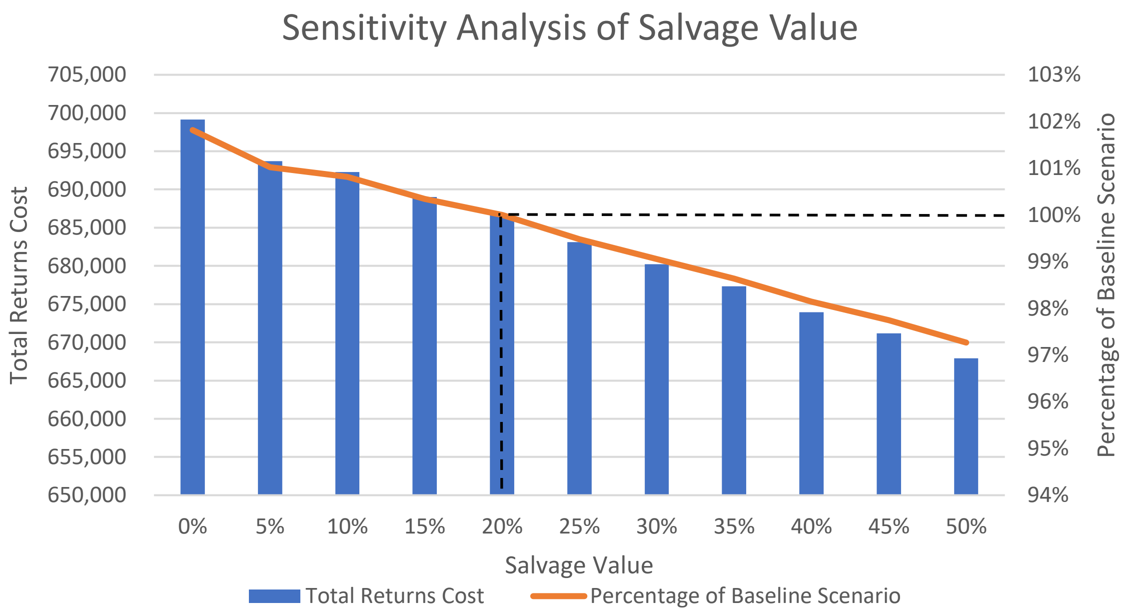
4.3.2 Salvage Value

Current salvage value is determined to be 20%. Through conducting a sensitivity analysis on the salvage value, it was found to follow a linear relationship with the total returns cost. Increasing the salvage value by 5% decreases the total returns cost by about 0.44%. Hence, efforts to increase salvage value of items should be encouraged only if the cost of the efforts is less than 3021 SGD/month (0.44% of 686,688 SGD a month) for each 5% increment.

Table 24: Sensitivity Analysis on Salvage Value

Scenario	Salvage Value	Total Returns Cost	% of Baseline Scenario
Baseline	10%	692,279	100.8%
Baseline	15%	689,020	100.3%
Baseline	20%	686,378	100.0%
Baseline	25%	683,126	99.5%
Baseline	30%	680,219	99.1%
Baseline	35%	677,331	98.6%
Baseline	40%	673,949	98.1%
Baseline	45%	671,192	97.7%
Baseline	50%	667,927	97.3%

Figure 34: Sensitivity Analysis of Salvage Value



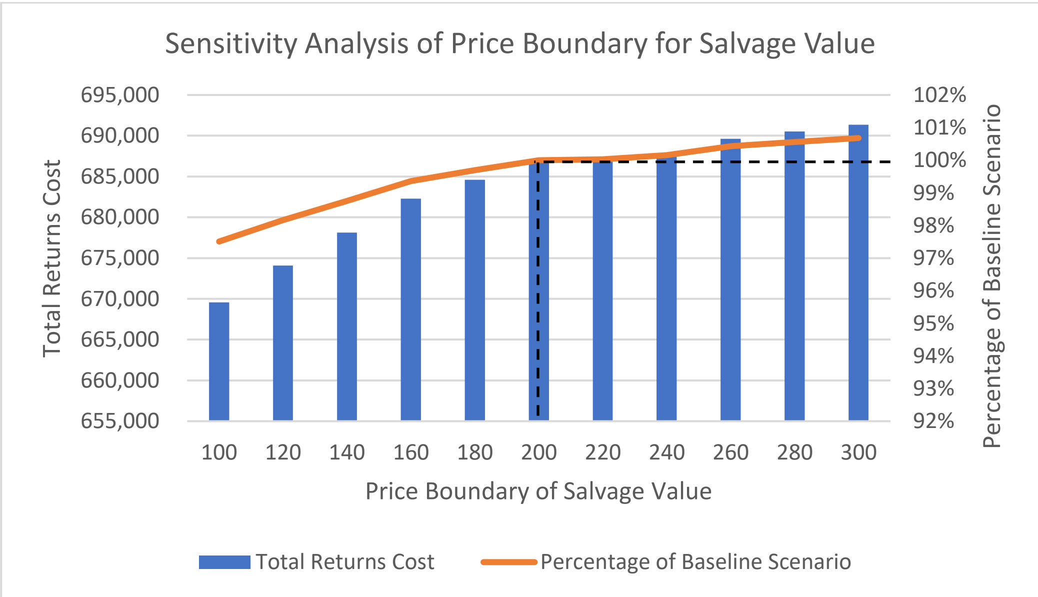
4.3.3 Price Boundary of items with salvage value

Current price boundary of items with salvage value is set at 200 SGD. A sensitivity analysis is conducted on the price boundary in Table 25 and Figure 35. The total returns cost is found to increase with a decreasing rate as price boundary increases. Hence, price boundary for items with salvage value should be kept at a maximum of 200 SGD and should be decreased if possible.

Table 25: Sensitivity Analysis on Price Boundary of items with Salvage Value

Scenario	Price Boundary for items with Salvage Value	Total Returns Cost	% of Baseline Scenario
Baseline	100	669,570	97.5%
Baseline	120	674,065	98.2%
Baseline	140	678,108	98.8%
Baseline	160	682,284	99.4%
Baseline	180	684,585	99.7%
Baseline	200	686,378	100.0%
Baseline	220	686,853	100.0%
Baseline	240	687,756	100.2%
Baseline	260	689,610	100.4%
Baseline	280	690,518	100.6%
Baseline	300	691,352	100.7%

Figure 35: Sensitivity Analysis on Price Boundary of items with Salvage Value



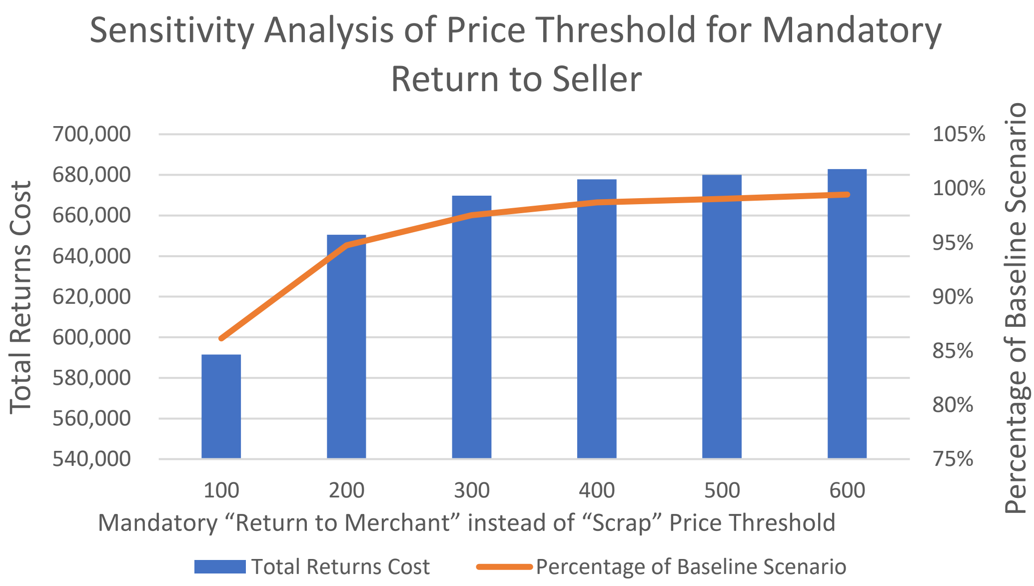
4.3.4 *Mandatory "Return to Merchant" instead of "Scrap" Price Threshold*

The relationship between the price threshold where items designated to be scraped will be sent back to seller instead and the total returns cost is in Table 26 and Figure 36. Total returns cost increases at a decreasing rate with the price threshold. Significant savings can be achieved with setting the mandatory "Return to Merchant" instead of "Scrap" Price Threshold to 100 SGD or 200 SGD, with savings of 14% and 5% respectively.

Table 26: Sensitivity Analysis of "Return to Merchant" instead of "Scrap" Price Threshold

Scenario	Mandatory "Return to Merchant" instead of "Scrap" Price Threshold	Total Returns Cost	% of Baseline Scenario
Baseline	100	591,548	86.15%
Baseline	200	650,538	94.74%
Baseline	300	669,688	97.52%
Baseline	400	677,752	98.70%
Baseline	500	680,021	99.03%
Baseline	600	682,794	99.43%

Figure 36: Sensitivity Analysis of "Return to Merchant" instead of "Scrap" Price Threshold



4.4 Maximizing the Salvage value of returned products

There lies a lot of value in the returned products. In the upcoming years, salvaging the proper value from these returned products will become an important lever in improving profitability. Currently, Lazada is able to extract 10-20% of the product value based on certain price threshold parameters. The online retailing industry currently averages a working percentage of 65-75%, with 20% of the goods in repairable condition and rest of the products have to scrapped. *(Working percentage refers to the saleable percentage of the goods returned.)* There is huge potential for Lazada in this space. There are several ways in which, this number can be pushed upwards; use cases of some are discussed below.

4.4.1 Long term contracts with third party vendors

Companies like AliExpress have contracts with third party companies who take care of the categorization, pallietization and selling these products at wholesale prices. In other words, outsourcing the total returns handling process by having fixed contracts with third party providers will allow Lazada to squeeze more out of the products by salvaging their value by leveraging the core competency of these vendors. This strategy can result in win-win situation for Lazada and the third party vendors. Lazada can focus on fulfilling the deliveries while the vendor focus specifically on extracting maximum value out of the returned products. The revenue sharing arrangement can be made on top of existing salvage value of ~15%. There are several innovative startups such as 'browntape' in this space that can help unleash the hidden potential in product returns market.

4.4.2 Leveraging the market for refurbished products

Flipkart and Amazon are cashing in on the market for refurbished products in India. As per the analyst report, the market currently stands at $6-8 billion (Menon, 2022). The market is specifically hot for categories ranging from electronics to apparels. Amazon has come up with 'Amazon Renewed' range to capture this market and is amongst the largest sellers of refurbished products. Lazada can identify the categories that have high working percentages and enter this area for increased salvage values.

4.4.3 Mystery Seller Audits

This initiative can indirectly help Lazada take control of the quality of products delivered by its sellers. In an novel move, Indian e-commerce player Snapdeal implemented its new inspection method of Mystery audits. This ensured that customers were being provided highest standard services and on the other hand ensured minimum returns. As an initial step, Lazada can identify top sellers with most returns and carry out mystery audits to deep-dive in the reasons for product returns. The sellers with high product return percentages can be kept under observation for a certain period of time. If the seller fails to imrpove upon the quality of products, we can consider dropping the seller for improved product quality and customer experience.

4.4.4 Tie-ups with spare part vendors

For specific categories with high spare part value, Lazada can have tie-ups with spare part vendors where disassembling the product and selling the components can help Lazada retreive 40-50% of the product value. Certain categories such as electronics can be handled this way. Retailers like Best Buy and Home Depot have deployed such techniques where they had technicians repair the returned products, and in case the product was beyond repair, help them retreive the raw materials that can be sold in the secondary market.

4.4.5 Give back to the society

For select categories like apparel, Lazada can decide to provide free merchandize to the needy. There are several startups in this space like Too Good To Go for food items that help restaurants to donate the surplus food to people in need. Along similar lines, Lazada can explore donating specific items for the people in need. This deed will help Lazada achieve goodwill and publicity for all the good reasons. It can even explore partnership with brands like Patagonia that embrace and publicize the used apparels. This can help Lazada push the goal of sustainability along with ensuring greater good for the society.

5. DISCUSSION

This project was proposed with the intention to reduce company's cost of handling returns. While we first started with building an optimization model for the process in mind, we soon realize that such a model is not applicable for Lazada's operations due to a lack of capacity constraints. We then decided to proceed with building a monte carlo simulation model to emulate the product returns process. To our delight, this method works well for us as it allows for the integration of decision algorithm with their associated cost.

Our partner, Lazada, was also pleased with the result, and had intended to implement some of the recommendations proposed. The simulation model enables them to identify potential cost savings to a decision, thus deciding how much the effort for the decision should cost. Also, sensitivity analysis allows for the determination of optimal value or range for the different parameters. A note of appreciation was received from Lazada in Appendix H.

While the result in the project follows very closely to actual numbers, several areas for improvement were identified in section 5.1.

5.1 Future Areas of Improvements

The total returns cost model has some limitations and could be improved with the following:

1. **Product Listed Price:** Actual selling price of items may not be accurately reflected, as sellers may artificially inflate selling price to highlight the discounted price of items on the platform as a marketing tactic. Only the listed usual price of items and not the discounted price of items is captured in the returns data.

2. **Actual Product Price:** Discounts offered and forward shipping cost of products are not captured in the computation of total returns cost. These should also be included in the cost model for a more comprehensive depiction of the cost impact. Incorporation of discount and forward shipping cost into the actual product price would improve accuracy of model.

3. **Actual Dimensions of Parcels:** Having the actual dimensions of parcels would allow for the computation of exact first and last mile shipping cost for each parcel. This information could then be used to determine the price thresholds for decisions dynamically for each item based on the inputs of actual dimensions of parcels, instead of a single price for each decision.

6. CONCLUSION

Most online retailers are currently focusing on optimizing their product returns as it could turn out to be instrumental in improving profitability and achieving competitive edge. Various attempts have been made to bring in efficiencies to reverse logistics, but most of them lack an end-to-end solution that will help a firm optimize its product returns.

Our research proposed to develop a monte carlo simulation cost model as a product returns management decision tool to help Lazada reduce its total returns cost. The cost model built in this project can be used to simulate changes in current processes or decision algorithm, reflecting expected cost impact that results from the changes. The model is thus helpful to conduct various scenarios to try and find the optimal price thresholds for each decision node. In the immediate future, Lazada can reduce its product return costs by **12%** and in the long run, there is a potential to reduce over **50%** of the product return costs. Furthermore, the tool will be helpful in identifying the cost trade-offs to improve certain parameters of the model. During the course of business, managers will face several decision dilemmas. This model can also be used to develop and evaluate alternative scenarios that Lazada may undertake to predict its total cost of returns.

Although developed specifically to suit the return processes of Lazada group, the model is modular to fit any reverse logistics network by tweaking some of the decision node parameters. We hope that this tool will enable the management of Lazada to make data-backed decisions resulting in efficiencies and reduced costs in reverse logistics.

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APPENDICES

Appendix A: Shipping Cost Rate Card

Shipping Cost Table 1

3PL 1	**Customer Returns First Mile Cost**			
	Direct Return to Merchant		**Non-Direct Return to Merchant**	
Shipping Fees	**Pick-up**	**Drop-off**	**Pick-up**	**Drop-off**
Gross Weight	**DEL & FD**	**DEL & FD**	**DEL & FD**	**DEL & FD**
2	X	X	X	X
3	X	X	X	X
4	X	X	X	X
5	X	X	X	X
6	X	X	X	X
7	X	X	X	X

3PL 2	**Customer Returns First Mile Cost**			
	Direct Return to Merchant		**Non-Direct Return to Merchant**	
Shipping Fees	**Pick-up**	**Drop-off**	**Pick-up**	**Drop-off**
Gross Weight	**DEL & FD**	**DEL & FD**	**DEL & FD**	**DEL & FD**
2	X	X	X	X
3	X	X	X	X
4	X	X	X	X
5	X	X	X	X
6	X	X	X	X
7	X	X	X	X

Shipping Cost Table 2

Shipping Fees	**Customer Returns Last Mile Cost**
Gross Weight	**DEL & FD**
2	X
3	X
4	X
5	X
6	X
7	X
8	X
9	X
10	X
11	X
12	X

**Numbers are masked or edited to conceal sensitive information*

Appendix B: Interview with Mr. Simon Eng (Lazada Group) on overview of Lazada Group

Interview with Lazada Group

01 Oct 2021

Overall Strategy of the group

Lazada group adopts the red ocean strategy due to the intense competition in SEA market and targets gain market share through providing the best service and price.

When Lazada Group started as South-East Asian's version of Amazon 9 years ago, it duplicates Amazon business model, and aims to capture the maximum market share and number of sellers. This business model proves to be successful as Lazada Group expanded to 6 South-East Asian countries. In 2016, the group was acquired by Alibaba as its regional goals matches Alibaba's expansion plan.

Today, Lazada strives to make business more sustainable as the ecommerce market at large in Singapore is not profitable. This proves to be a difficult task with competitors having very strong financial backing competing for market share based on pricing. Lazada hopes to work with other ecommerce partners to make the market more sustainable instead of competing via price.

Overview of Lazada in Singapore context

Today, Lazada and Shopee are two of the biggest ecommerce platforms in Singapore with a total estimated market share of 60 to 70%. During the pandemic however, a lot of smaller businesses and shopping malls had started an online presence with their own selling site, increasing competition.

Lazada currently has an order volume between 80,000 to 100,000 daily in Singapore. Among them, the return rate is about 1.02-1.05%. The top selling categories of products depends on season and marketing campaign. During campaign, high-value items such as electronics would be the top sellers while groceries are the daily top-selling products.

QA Department’s objectives

The 6 Lazada values:

1. Customers first, employees second, shareholders third
2. Trust makes everything simple
3. Change is the only constant
4. Today's best performance is tomorrow's baseline
5. If not now, when? if not me, who?
6. Live seriously, work happily

Main objectives of the QA department:

1. Ensure customer experience (in line with No. 1 of Lazada values)
2. Minimize logistic cost in product returns

QA Department’s KPIs

1. Lead time from the time return is initiated to refunding customers.

2. Net Promotion Score (NPS).

Email is sent to approximately 10% of customers to get a review on Lazada's performance. Some of the questions include:

- How likely are they to recommend Lazada to others?
- Which aspect of the shopping experience is the main reason for your score? (Product return experience is listed as an option)
- How does Lazada perform as compared to other competitors in this aspect?

3. Cost.

Lowering cost of product return operations and identifying areas of loss.

For example:

- Identifying the percentage of returns that can be salvaged, are refunded, discarded, or rejected.
- Reduce first mile logistic cost for returned items. There are differing rate card for the different 3PL services engaged. Without having to pay for them, customers tend to choose the ones with better service, which often cost more. (The QA team is currently working on reducing cost by specifying parcel drop-off locations instead of arranging parcel pick-ups for product return.)
- Reduce high-value products in good condition scrapped due to inaccurate quality check results, thus reducing loss.

Process Flow of Forward Logistics

There are 3 main types of logistics flow for products, mainly Cross-Border, Marketplace, and Retail products.

The forward logistic flow for each main category is as below.

Cross-Border:

Cross-Border products are items sold by an overseas seller to the Singapore market.

After customer placed an order, the overseas seller would send the item to a consolidated warehouse in seller's country. Lazada would arrange for the linehaul, and custom clearance in China and Singapore. After which, items are released to a local 3PL company to do the sorting and delivery.

Marketplace:

Marketplace products are items sold by a local seller to the Singapore market.

After customer placed an order, seller would drop-off item or arrange pick-up with a 3PL company. The 3PL would bring the item to their warehouse, and sort and deliver accordingly.

Retail:

Retail products are items sold by Lazada and stored as inventory in its fulfilment centre.

After customer placed an order, picking would be done in the fulfilment centre. After completing the orders, they are sent to the 3PL to sort and deliver.

Operations

The sales channel for Lazada is nearly 100% through online platform, with occasional showcase held for big brands. These showcases however, are not too successful in translating to orders.

Payments are nearly all done through online payment. Cash-on-delivery is uncommon in Singapore.

Concerns of forward logistics

Scalability:

- Can big brands have their product stored at Lazada to reduce delivery lead time?
- First and last mile delivery for an order is currently done by the same 3PL vendor. If Lazada have their own sorting facility, there can be a mix-and-match of first and last mile 3PL vendors.

Process Flow of Reverse Logistics

The first mile reverse logistics flow process is the same for all products. Customers have the option to drop-off or to arrange for a courier pick-up for the item they are returning. Of these returned products, about 90% are sent back to Lazada's local warehouse whereas the rest are directly sent back to local sellers.

Products returned to warehouse would first undergo a quality check before a decision is made on its handling.

Cross-Border:

If an item is to be sent back to its overseas seller, Lazada will consolidate the items, arrange for a linehaul to bring the item back to the seller's country and have a 3PL located there to distribute the items back to their sellers. Sellers will usually refund the product amount to Lazada.

Marketplace:

For items to be sent back to its local sellers, Lazada will have the items sent back by a 3PL (Singpost). Sellers will usually refund the product amount to Lazada.

Retail:

For items sold from the fulfilment centre, if they are unopened, they can be resold to the next customer.

Difficulties faced in product return management

1. *Unsustainable practices to maintain good customer experience.*
   If an item is deemed to be an invalid return after the quality check process, item should be returned to customer. This, however, is often not carried out to prevent bad customer experience. In addition, the local ecommerce market often tolerates such invalid return, adding to Lazada's reluctance to be the first in the market to enforce strict return policies, driving away consumers. Such practices are unsustainable, and cost incurred will add to running operational cost.

2. *Algorithm requiring human intervention to reduce poor decisions.*

In the current product return decision algorithm, human intervention is often required to prevent poor customer experience. The refund reason selected by customer may not be accepted by the algorithm due to a failure to reconcile refund reason and actual product condition. For example, a customer that selected the return reason as "wrong size" for an apparel may be returning the item because it does not fit him/her. However, the algorithm may reject the return and decide to send the returned product back to customer after finding no mismatch between the size of product sent and the size ordered. This in turn requires human intervention or will otherwise result in poor customer experience and additional delivery cost. This is also one of the current projects undertaken by the Quality Assurance team.

3. *Electronics is the most challenging return product category.*
   They often take the longest time for quality check due to the time needed to run the items and identify the problems as raised by customers. And as high-value items, the loss incurred from these returned products are the highest. In contrast, fashion product is often straightforward with the quality check results determined in a short span of time. The same challenge is believed to be experienced by competitors in Singapore.

4. *Return policies are relaxed to remain competitive*
   Compared to brick-and-mortar store, online customers could not try out items. Hence return policies are required to attract customers to purchase products online. In addition, fashion ecommerce retailers are very aggressive in their marketing and have very relaxed return policies. To gain a bigger market share, Lazada, which too has an apparel section, needs to maintain a similarly relaxed return policy to be competitive.

5. *Unclear cost effect of direct product return to local sellers*
   Direct return to local sellers is dependent on prior policy and agreement with local merchant. While there is a saving on the cost of quality check process by Lazada, the transport cost of direct return to seller is more expensive by SGD 1 for each delivery. Also, if the local merchant rejects the refund, Lazada will not be able to recover any amount as they can neither reject and send the returned product back to customer, yet needing to refund the customer, nor can they resell the items to reclaim its salvage value. Hence, there is a dilemma on whether direct return to local seller decreases or increases cost in the long-term.

6. *Unidentified product categories for returned product*
   Returned products are currently not categorised. This is a project that the Quality Assurance team is currently working on.

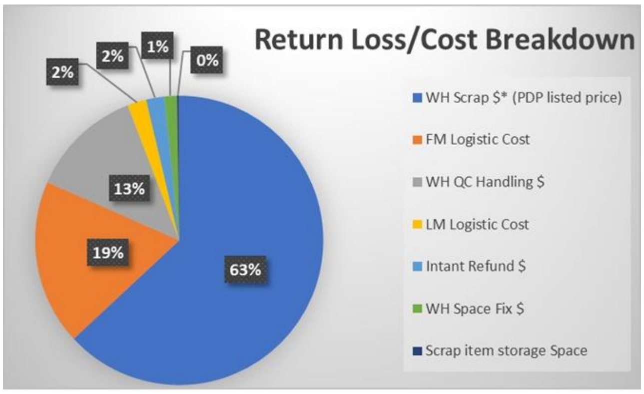
<u>Major cost components in the product return process</u>

Cost of returned product scrapped: 63%

Cost of first mile logistic: 19%

Cost of quality check handling: 13%

Other cost components: last mile delivery, warehouse storage space, etc



Lazada Singapore Return Cost Breakdown (April-August 2021)

Logistic Service Levels

Forward logistic

The delivery of groceries from redmart (the supermarket arm of Lazada) needs to follow a delivery slot as groceries cannot be unplanned. Redmart has an appointed 3PL for its delivery service.

The delivery requirement of other items from Lazada is to be as fast as possible, with differing requirements based on the source of shipment. Customers can also choose different shipping fee options for their delivery (e.g., express/economy for Cross-Border products)

Refund process

There are 3 main types of return:

1. Instant Refund:

Cancellation of order before item is shipped out. The refund process will be immediate.

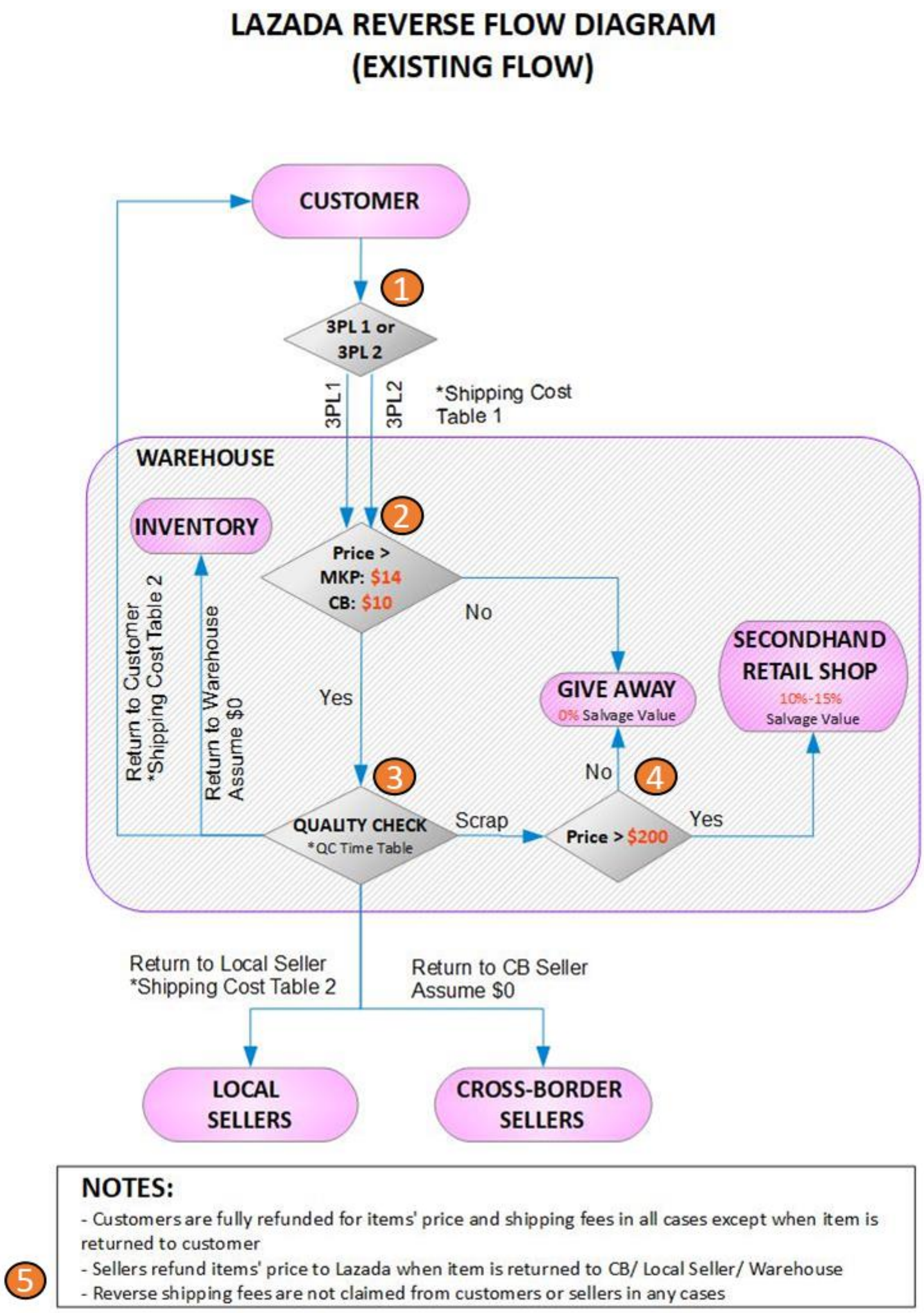
2. Easy Return:

For low-value item. Items are either refunded without collecting back to warehouse or when customer drop item off at its drop-off point. This applies to selected customer with clean return record to ensure no abuse of the refund system. The refund process is almost immediate.

3. Normal Returns:

Once refund is initiated, item pick-up/drop-off needs to be arranged within 5 days. After which, item is sent back to warehouse within the next 5 days, and quality check will take place within the next 2 days. Hence, the full refund process is required to be completed within 12 days. However, to improve customer experience, the refund process is often quickened.

Appendix C: Interview with Mr. Simon Eng (Lazada Group) on current return processes



1

- Customer initiates the return process on Lazada App/website, and they can choose one of the following options:
  - Pick-up by 3PL 1/ Drop-off by 3PL1/ Drop-off by 3PL2
    (3PL1 currently handles 85% of the returns and 3PL2 handles 15%)
  - Except for bulky items which are sent and returned directly to sellers by customers
- Lazada is using the ease of pick-up by 3PL as an advantage and selling point compared to competitors.
- Below items which met criteria of Biz Risk team are not collected when return is initiated, and fully refunded to customer. (Exact criteria are not made known.)
  - Items that exceed return period
  - Items which met criteria of Biz Risk team (Exact criteria are not made known, but along the lines of very low value items and customer with good purchase record) (Approximately 4-5% of returns by volume)
- QC team is open to having an option of "No Collection" with price threshold but is concerned with potential issues of customer abusing the system.

2

- Cost boundaries were decided by QC team after comparing estimated cost of doing QC, percentage of items returned to sellers and shipping cost, against amount that can be claimed from sellers.
- All price boundaries are open to changes as long as it is supported.

3

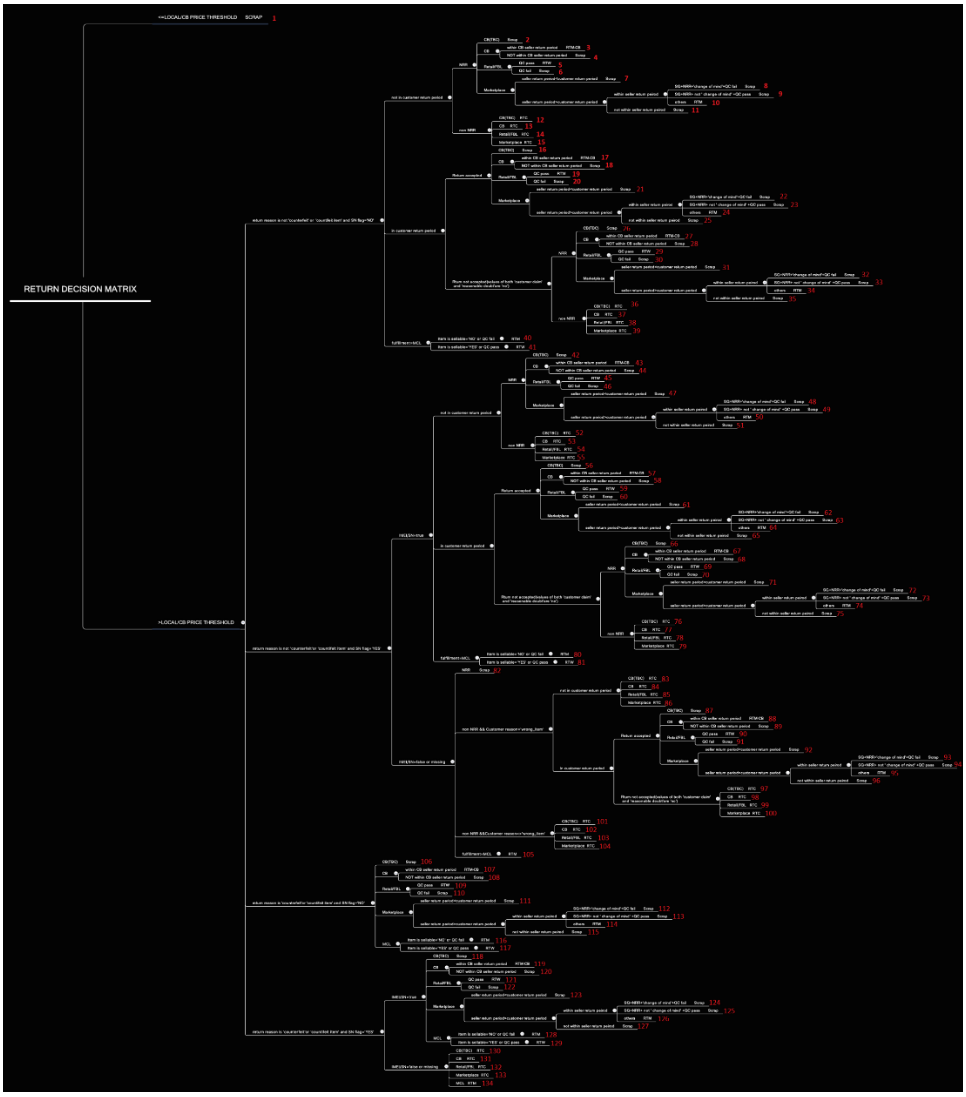
- Quality Check process is outsourced to vendors and charged a fixed price per item, regardless of type and size. There is no capacity limit. QC team forecast the estimated return volume for the next month and inform vendor.

4

- $200 price boundary determined by current bidding vendors who are only willing to pay for items with value above $200
- Vendors currently have an agreement with Lazada to not let buyers know that the items were scrapped items from Lazada
- Lazada is open to alternative secondary market with higher salvage value but is concerned with potential issues of brand tarnishing and backlash from brand names for selling lower-priced items.
- Items above $200 are filtered in a list and no manpower cost shall be considered for this process

5

- Lazada is looking to charge sellers for the reverse shipping cost but that would be a difficult process as there are different agreements with different sellers and shipping cost.



How the algorithm was developed

- Current algorithm was developed with branches added by request from different departments
- Some of the initial purpose and intention of the algorithm branches were lost
- For example, 'NRR' and 'MCL' branches can be ignored.

Current use of algorithm

- Algorithm is currently in use and followed except in cases where the outcome is "Return to Customer".
- In such cases, to prevent dissatisfactory customer experience, product will be checked again manually to ensure that there is a legit reason to return item to customer.

New algorithm

- QC team would like the new algorithm to be developed from the current algorithm
- Branches that does not make good sense shall be eliminated based on our judgement calls

	Forward Logistic Cost	Product Selling Price	Reverse Logistic Cost
Return to Customer	Customer	Customer	Lazada
Return to Local Seller	Lazada	Seller	Lazada
Return to Cross-Border Seller	Lazada	Seller	Lazada
Return to Warehouse	Lazada	Seller	Lazada
Scrap	Lazada	Lazada	Lazada

Appendix D: 2021 Returns Data from Lazada – Sample Data

Month	Return Number	Product Name	Product unit price	Fulfilment Type	QC Date	QC Result	Logistic Closure Outcome	Reasonable Doubt	Customer Claim Valid or not	Customer Return Reason One	Customer Return Reason Two	IMEI/Serial Number matched	Actual Serial Number
Jan-21	10515521444617	XXX	31	crossborder			scrap	FALSE	FALSE	does_not_match_description_picture	does_not_match_picture		
Jan-21	650062616190852	XXX	470	retail/fbl	18/9/2020 16:13	fail	scrap	FALSE	FALSE	do_not_want_or_does_not_suit	do_not_want		SDMPD3LB9MF3P
Feb-21	10250840906427	XXX	26	crossborder			scrap	FALSE	FALSE	counterfeit_item			
Feb-21	10258022831835	XXX	18.45	crossborder			scrap	FALSE	FALSE	does_not_match_description_picture	does_not_match_picture		
Feb-21	10265207056014	XXX	12.84	crossborder			scrap	FALSE	FALSE	received_wrong_item			
Mar-21	650477213298527	XXX	38	crossborder	16/3/2021 18:32	fail	return_to_merchant	FALSE	FALSE	missing_accessory_freebie			
Mar-21	650490714509578	XXX	6	crossborder	17/3/2021 13:06	fail	scrap	FALSE	FALSE	does_not_match_description_picture	does_not_match_description		
Mar-21	650490714509578	XXX	6	crossborder	17/3/2021 13:07	fail	scrap	FALSE	FALSE	does_not_match_description_picture	does_not_match_description		
Mar-21	650477810849224	XXX	15.9	retail/fbl	16/3/2021 15:05	fail	scrap	FALSE	FALSE	received_wrong_item			
Mar-21	650477213715670	XXX	34.9	marketplace	17/3/2021 11:25	fail	return_to_merchant	FALSE	FALSE	damaged_faulty_item	item_physically_damaged		

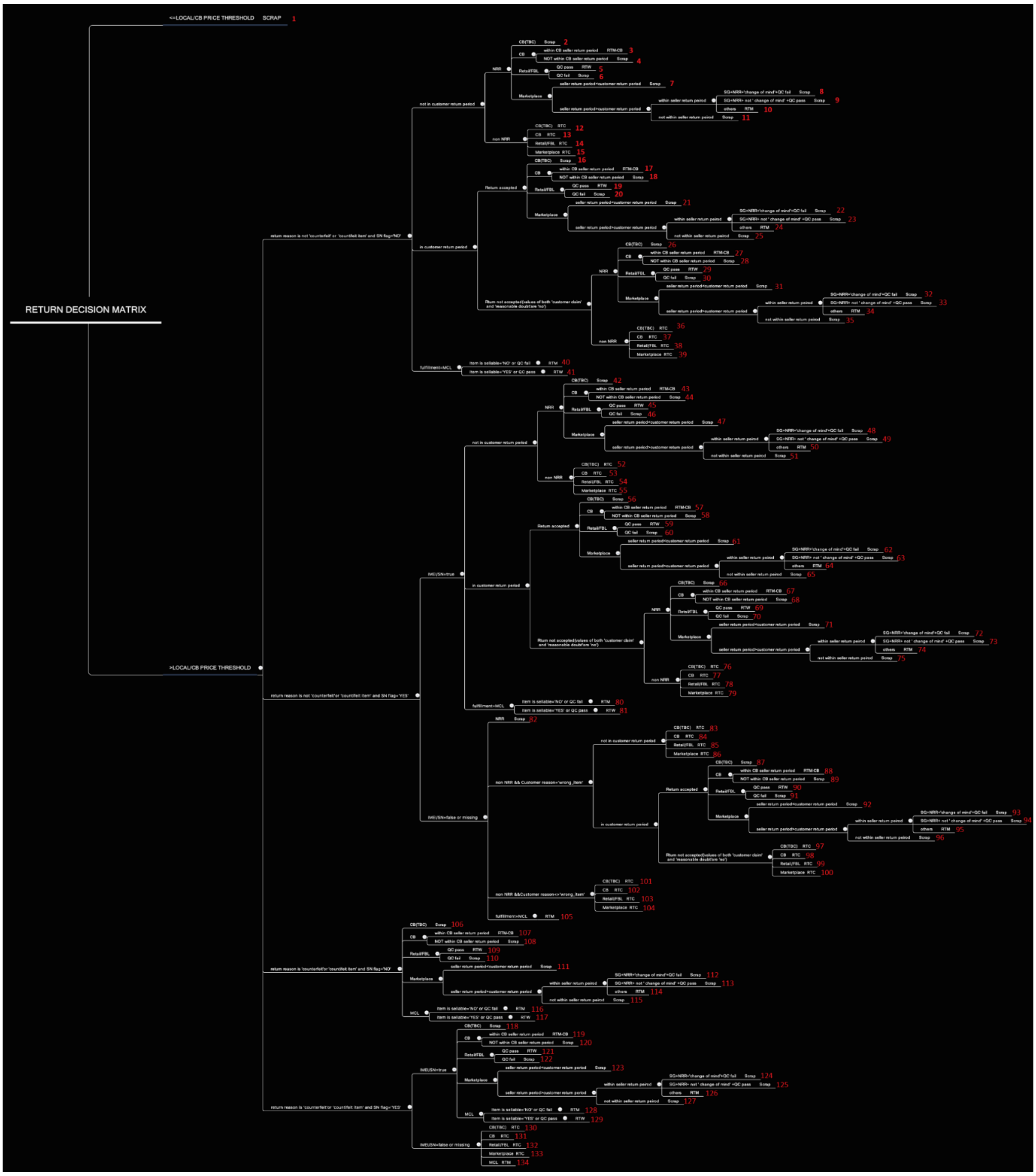
*Disclaimer: Some data are masked due to confidentiality

Appendix E: 2021 Returns Financial Data from Lazada – Sample Data

	Non-DRTM Item	% simplified QC	QC handling	Pallet (5.6)+ Work station Space	Total Cost	$ Per item	RTM/RTW	RTC	SCRAP	%SCRAP	FIRST MILE 3PL	FIRST MILE 3P	LAST MILE	RTM	Scrap
June	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX
July	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX
Aug	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX
Sept	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX
Oct	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX
Nov	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX
Dec	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX
Jan	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX
Feb	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX	XXX					

**Numbers are masked or edited to conceal sensitive information*

Appendix F: Existing Return Decision Matrix



Appendix G: Return Decision Algorithm in Python

Structure of Code:

Table of contents

Libraries

Decision Algorithm function

- Existing Algorithm
- Clean Algorithm
- Scenario 1: Review and revise decision outcomes
- Scenario 2: Pegging Seller's Return Period to Customer's Return Period
- Scenario 2a: Pegging Local Seller's Return Period to Customer's Return Period
- Scenario 3: No Collection for items to be scrapped without QC
- Scenario 4: Anything above 200 SGD will be returned to merchant
- Scenario 5: Combination of Scenario 1, 2a, 4

Importing Historical Dataset

Generate Dataset

- Plot generated dataframe

**Actual code is not shown to conceal sensitive information*

Appendix H: Note of Appreciation from Lazada Group

Felicia Suat Teng Chen

From:	Simon Eng <simon.eng@lazada.sg>
Sent:	Thursday, 5 May 2022 12:47 AM
To:	Felicia Suat Teng Chen; Tejinder Singh
Cc:	Edgar Gutierrez-Franco
Subject:	Note of Appreciation

Hi MIT team,

I am writing this to congratulate you on the completion of your capstone project.

We are pleasantly surprised with the results and see a lot of value addition to our existing product returns management process. From this project, we have also gained insights into potential areas for cost savings that we will further delve into.

The model built in the project is a good decision support tool that will enable us to make data-backed decisions in managing returns to reduce the total cost of returns. Moreover, this model will aid us in evaluating various strategy decisions by exhibiting the potential cost benefits.

We will be implementing some of the proposed recommendations and we look forward to sharing the results with you.
Our team at Lazada would like to thank you for your work and we wish you all the best!

Best regards,
Simon Eng
VP Quality Assurance for Lazada Singapore and RedMart

“We are pleasantly surprised with the results and see a lot of value addition to our existing product returns management process. From this project, we have also gained insights into potential areas for cost savings that we will further delve into.

The model built in the project is a good decision support tool that will enable us to make data-backed decisions in managing returns to reduce the total cost of returns. Moreover, this model will aid us in evaluating various strategy decisions by exhibiting the potential cost benefits.”

- **SIMON ENG**, VP Quality Assurance, Lazada Singapore