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MSc Dissertation

Developing agent-based model to describe customer decision-making about product return

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This project is entirely the original work of student registration number 31711995. I declare that this dissertation is my own work and that where the material is obtained from published or unpublished works, this has been fully acknowledged in the references. This dissertation may include material from my own work from a research proposal that has been previously submitted for assessment for this program.

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ABSTRACT

As a result of the COVID-19 pandemic and the rise of online shopping in the clothing industry, return services are becoming one of the most crucial aspects of customer service. Many retailers face the unavoidable challenge of return service costs. This is a difficulty in analysing consumer decisions. This dissertation aims to describe customer decisions regarding product returns to generate results for agent-based modelling (ABMS) simulations of consumer behaviour under conditions such as retailer's return policies. The structure of the agent-based simulation model is based on a literature review on product returns in omnichannel, consumer decisions regarding returns, and agent-based simulation modelling. The agent-based model simulation represents the results of consumer decisions in each state. There is decision-making that has been made in the model framework development process. However, some decisions establish beyond the scope of the standard return process. This leads to an analysis of consumer behaviour or decision-making that impacts the return process by making these decisions due to a process in which customers change their minds or specific customers place bracketing orders on purpose. This resulted in the discovery of a fascinating return decision. This enables this study to explain consumer decision-making concerning various aspects of the return process.

Keywords: Product return; Decision-making; agent-based simulation

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I would like to express my sincere appreciation to my supervisor, Dr Steffen Bayer and professor in team Dr Regina Frei, and Dr Danni Zhang for their continuing support, extensive knowledge, provision of data from an existing survey, and invaluable dissertation advice. In addition, I would like to thank my parents for their continuous encouragement and support.

CONTENTS

ABBREVIATION

ABBREVIATION	FULL NAME
ABS	Agent-based simulation
ABM	Agent-based model
ABMS	Agent-based model simulation
BOPS	Buy Online and Pick up in-Store
BORP	Buy Online, Return to a Physical store
CB	Consumer Behaviour
CLSC	Closed-Loop Supply Chain
RC	Return Centre
PE	Planning and Execution
RM	Return Management
RP	Return Policy
UK	United Kingdom
UML	Unified Modelling Language
UPS	United Parcel Service company

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CHAPTER 1. INTRODUCTION

This chapter introduces the background and significance of the dissertation topic. Next, the study's aims are stated, followed by the study's scope and the dissertation's structure.

1.1 Background information and motivation

Due to the COVID-19 crisis, the number of online shopping has increased dramatically, and many retailers in the e-commerce business are increasingly competitive and challenged, especially the clothing business (Nanda, et al., 2021). The clothes business has to offer the best products and services to attract customers. From a customer's perspective, shopping online gives them more freedom to shop and compare prices (Wolfinbarger and Gilly, 2001); however, the major downside is that they cannot directly try the product like when they shop in-store. Even if a store offers pictures, videos, and descriptions, it does not give customers the confidence to meet the customer's expectations. To be fair to customers and to provide the best service to compete in the business. Therefore, online clothing stores have a product return service (Walsh, and Möhring, 2017). Undoubtedly, product return service in online clothing stores is inevitable. According to statistics, the clothing business has the most product return compared to other online sales businesses (Levin, et al., 2003). However, return decisions can be very difficult to determine because they involve many manual steps, such as how customers make decisions in different situations and how each segment is handled. Thus, this dissertation developed the Agent-Based model simulation (ABMS) model to describe customer decision-making about product returns. The agent-based simulation could explain how decisions are made and also simulate thousands of people in realistic environments with highly detailed internal physiology, perceptions, and the ability to process those perceptions to make decisions based on them. A person can decide what to do, using logic and simple reasoning (DeAngelis, and Diaz, 2019). Therefore, agent-based model simulation is appropriate for returns in a multichannel apparel business with diverse consumers and varying product return expectations and for establishing the manufacturer's return policy, which impacts consumers (Backs, et al., 2021).

The motivation for this project was that the researchers were studying in the United Kingdom during the COVID-19 period. The United Kingdom has a climate different from the countries in Asia where the researcher former residence. It makes it necessary to buy more items, especially clothes., so buying shirts has to use online channels. Furthermore, when purchasing online, especially in the apparel category, it is not as expected in various fields. Therefore, it is necessary to return the product to the system available in the United Kingdom. What led the researcher to switch from a person who never returned using a return service to produce service in the UK because most return policies were convenient and free of charge was incredibly encouraging. More variety of reasons to return. Therefore, it is interesting to study the decision-making and behaviour of customers in the decision to return the product—any return factors so that the store or the retailer can be evaluated and analysed. Consumer judgement to reduce return costs or adjust the policy to satisfy both customers and sellers. The outline of the approach/methodology of this project starts from researching various aspects of the return of products to analyse and convert it into the decision of the consumer to return the product.

Subsequently, find additional data from "Product Return in a COVID-19 World-Jan 2022" to infer the necessary data from the survey, thus creating a flowchart diagram of consumer decision-making made from many conditions and cases where possible by collecting information. Once we obtained the proper flow, it was applied to create a stat chart in the AnyLogic simulation program. Finally, we simulated the agent-based model to describe the consumer's product return decision.

1.2 Dissertation objectives and research questions

This research aims to conduct an agent-based model (ABMS) to describe customer decisions regarding customer return decisions. Agent-based models focus on individuals. The model refers to how individuals determine when and how to act. Individuals follow various procedures (rules) when selecting alternatives. Most ABMs explicitly account for the influence of the individuals with whom the individual interacts. A crucial aspect of agent-based modelling is the description of the decision-making and social interaction mechanisms. Although theories of choice, action, and social interaction are required at this stage of the modelling procedure, the extent to which behavioural approaches are utilised in ABMs varies substantially. Even when identical individuals are in the same context, random factors still cause differences in their decision-making and social interaction processes (Klabunde and Willekens, 2016). Therefore, this study aims to describe the customer's decision regarding returns. For the benefit of understanding consumers' decision-making, reasons and conditions for returning products, this project can further develop this research into a strategy or policy for planning a return system that emphasises understanding consumer behaviour.

1.3 Scope of study

The dissertation used secondary data from our existing consumer behaviour survey, "Product Return in a COVID-19 World-Jan 2022," which is only available in Qualtrics by Dr Danni Zhang and others with permission. The data comes from published research sources to set the parameters for the ABMS simulation model. The focus group is the multichannel apparel business and creating simulation models using AnyLogic version 8.7.7.

1.4 The general structure of the dissertation

The dissertation will be structured as follows. Chapter 2 provides an overview of product return in omnichannel retail, Customer decision-making in product purchase and return, The Agent-based modelling, and Empirical studies of Agent-Based model simulation (ABMS) about consumer decision-making of existing research published in related areas and similar work. In chapter 3 provides a methodology consist of data analysis, design customer decision-making about product return flowchart, and develop agent-based model simulation. Then chapter 4 in result and analysis, chapter 5. Discussion and limitation, and Chapter 6. Conclusion and recommendation

CHAPTER 2. LITERATURE REVIEW

The primary purpose of this literature review is to explore comparative research and other similar work that has been done in the past. This will help inform the methodology for the project, evaluate the suggested approaches, and find potential problems that can be avoided.

The literature review starts with product returns in omnichannel retail, including the product return process, problems, and customer decision-making in product purchase and return. Then, there is similar work of agent-based simulation.

2.1 Product return in omnichannel retail

Literature on product returns in online and offline channels, or omnichannel, is spread out in many branches with different solutions. Omnichannel retail usually uses various sales channels. The term "omnichannel" refers to the retailer's offering a seamless experience across the various channels, which will then seamlessly complete the order over their devices (Rodríguez, et al., 2020). Retailers across all price points have adopted very similar policies and practices and experienced very similar issues, according to their study of multichannel and omnichannel strategies used by fashion and apparel retailers. However, customers who are unsatisfied with their purchase are offered the opportunity to request a refund of their money if they return the merchandise within the allotted amount of time. Customers feel less anxious about their purchases before they make them when they have access to customer-friendly return policies (Acquila and Chaparro, 2020). If you want to manage return policies well, you need to know more about how customers react to return policies. Although most retail establishments have return policies, the policies offered by some stores are more generous than those provided by others. The conventional wisdom holds that customer-friendly return policies are more likely to result in purchases than they are to promote product exchanges. The leniency of return policies has been broken down into five categories: time, money, effort, scope, and exchange (Guide, et al., 2006).

When returning things by post or courier, customers must correctly fill out the return slips provided to them. Retailers could encourage customers to comply with store policies by giving some form of advantage in exchange for a truthful return code (Abdulla, et al., 2019). In most cases, the paperwork also shows why the customer wants to return the item. The study identified the following reasons that affect customer returns: "The Customer Received the Wrong Product" means that the customer received a product that does not match the order, including the product code and description. Studies that are still being done show that more than 20% of product returns are because the wrong item was sent (Jenny, 2021). Most of the time, this is because of problems with pick-and-pack during fulfilment. This has a significant impact on both the quality of the customer experience and the rate of customer loss.

"The Items Arrived Damaged or Defective" are described as defective products or signs of damage that occur before the product reaches the customer. For this reason, it is essential to check the product's quality to ensure that it is in the proper condition before delivery. Moreover, it should have to identify the cause of the damage, whether it is caused. Studies also show that another 20% of product returns are made because the item was damaged in transit (Wallenburg, et al., 2021). Therefore, when it comes to quality, packaging, and transportation, knowing which things are being damaged in transit helps you identify chances for improvement. "The Product Doesn't Match the Website Representation" is essential when describing the products on the website. product photos This is mainly due to incomplete product descriptions, so customers are often dissatisfied when they receive an item that doesn't match what they saw while shopping on the website. This will also affect e-commerce store reviews (Ristoski, et al., 2018).

"Size and fit"; although many online retailers have listed a comprehensive product size guide in their product descriptions, they might not be exact for every customer. It is difficult to accurately determine the actual size of all customers because different factories or brands have different designs and sizes (Serravalle, et al., 2022). "Bracketing" refers to purchasing multiple different sizes or colours of an article of clothing to return the majority of the item; this directly affects the operator as it is certain that the product return will occur. Many products are returned frequently (Xu, et al., 2022). "Product Quality Did Not Meet the Customer's Expectations" Since each consumer's quality standards are unique, determining whether or not a return was warranted due to poor quality is one of the most challenging tasks. Some customers get used to imagining what the product will look like after reading the description. This directly impacts the purchase of the product, and upon receipt of the product, they are disappointed with the quality of the product (Matzler and Hinterhuber, 1998). "Wardrobing/Returns Fraud" according to research that was published, the amount of money lost to fraudulent return claims climbed by 35% from 2018 to 2019, totalling almost $27 billion. Regrettably, not all customers are trustworthy, and a significant number of them take advantage of today's lenient return policies and dogged dedication to satisfying their needs. Retailers who do not demand a receipt or other proof of purchase are particularly susceptible to fraud (Shih, et al., 2021)

According to Jin et al. (2020), the research retailers' strategic decisions regarding the BORP policy implementation are explained by the "buy online, return to a physical store" option (BORP). When a store adopts the BORP policy, they simulate a duopoly in which each store maintains both an online and a physical channel. They consider model features such as customers' purchase and return behaviour across channels, consumer heterogeneity, and retailers' channel efficiency in managing product returns. The chance of product incompatibility and return is included in consumer purchase decisions. Modelling customers' retailer brand preferences and variances in their physical shopping and return expenses account for consumer heterogeneity. They model supply chain interactions using a multistage game framework. The results reveal that shops that employ the BORP option achieve equilibrium when their products are sufficiently differentiated, and their physical channel is much more efficient than their online channel at salvaging product returns (Xu, et al., 2021). The correlation between the profit-increasing and profit-decreasing effects of the BORP policy is the primary factor influencing these outcomes. This research suggests that return policies require consideration of the form of return. Cost and return times affect the whole business of the store. Therefore, the return policy must simultaneously consider the cost effect and impact on customer satisfaction (Li, et al., 2013). Setting up a suitable return policy helps to control the store's costs and increases the business opportunity, which is as important as a business strategy.

2.1.1 The process of product return

The procedures for returns in retail are pretty complicated. Even though time is frequently of the essence if products are to be reinstated to the store, they often involve several different policies, places, and people. For example, a product whose design doesn't match the store's guide size. A product whose colour is wrong from a promotional photo shoot. Or the products that are below the customer's expectations. These products have a higher risk of return (Jeng, 2017). The following description of the generic process is a synthesis of the techniques observed in the companies used for the case study and confirmed with various other companies. Although every business will have similar inbound and outbound, some processes may differ slightly. The return process starts with the customer's order being selected for delivery to an address or pick-up at the store. After an order has occurred, there is a possibility that the customer changes his mind and cancels the order (Piotrowicz and Cuthbertson, 2019). If the customer cancels the order in time before the package is prepared for delivery, a refund will be processed immediately. However, if the customer cancels too late after the package has been prepared for delivery, the customer must proceed to the return point. From the observations, several points enter the return process. Customers can return their purchases in many ways. Returns via courier, post office, parcel shop, or automatic drop box Include contacting customer service via email or phone to request a refund without returning the product. However, not all items are refundable, and some of the product returns might be rejected, depending on the discretion of the company's policy. Products returned due to non-customer damage may be returned to the manufacturer or factory for further repair or recycling, as shown in figure 1 (Frei, et al., 2022).

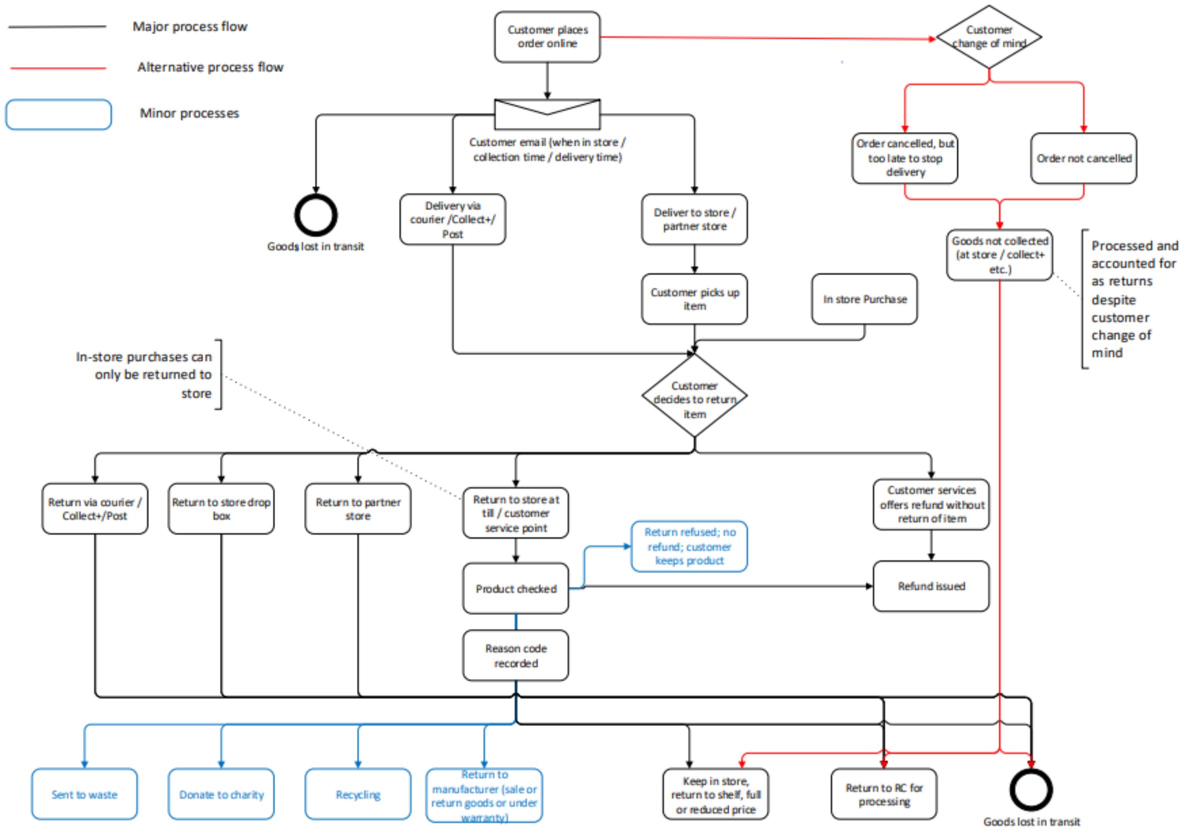

Figure 1: The product return process by (Frei, et al., 2022).

2.1.2 The product return problem

Returns product is a significant issue for online retailers, as at least 30% of all online products are returned, compared to only 9% of physical store transactions (Reagan, 2016). In particular product categories, such as apparel and home furnishings, where online buying has disadvantages, return rates might be significant. However, many retailers and manufacturers are unaware of this issue's importance. The return process can be very complicated. As online retailers try to meet customer satisfaction in the service competition, e-commerce overgrows. Since the pandemic's start, many merchants have been trying to establish sales channels on more than one platform to solve the crisis they face. They need to connect online and offline shopping channels. Providing excellent customer service is a crucial aspect of increasing sales. However, providing outstanding service will increase sales and generate more engagement and followers on their online channels, which is the key to their success in the way they do it (Rahman, et al., 2018). Many stores offer free shipping and multiple ways to return items. They try to provide the best service to be superior to competitors for a competitive advantage. It also provides a free return service for customers, which has resulted in better customer engagement and feedback than expected. However, they cannot accurately estimate the actual business return with the additional cost of the return process. This can lead to retail losses. This puts many problems with returns in the wrong direction (Frei, et al., 2022).

In the last couple of years, e-commerce retailers have rapidly grown. Studies have shown that about one-third of all online purchases are returned (Petersen and Kumar, 2009). In today's competitive market, more and more stores are implementing "hassle-free return" policies, which improve customer engagement, overall spending, purchase rate, customer satisfaction, and future buying behaviour. But a high return rate means the profit margin will be smaller if you have a generous return policy. The effect of direct return costs and indirect costs caused profits to be reduced by 3.8% on average per retailer or manufacturer (Pei and Paswan, 2018). That has become a significant challenge for the e-commerce industry and has even caused many online retailers to fail to manage a return solution. Because of this, the company must be able to predict what customers will do when they consider looking at products or putting the item in their shopping cart and stopping bad transactions. But product purchase and return records from the past have a lot of helpful information that can be hard to combine logically to predict future returns (Zhu, et al., 2018).

2.2 Customer decision-making in product purchase and return

The purchasing behaviour of consumers is a significant factor in determining a business's level of market competitiveness and increasing the likelihood of successfully attracting new clients. Companies that keep track of their customers' purchases and preferences across all their interactions have a more significant opportunity to meet the customer's needs (Ghosh and Banerjee, 2020). Several researchers have attempted to study the possibility of predicting customer purchasing behaviour within e-commerce or multichannel retailers. Before consumers decide to buy apparel or fashion items online, they search the market and evaluate it systematically based on their experience to find the best option in terms of design, price, promotion, time, delivery, and reliability. However, consumers cannot collect and analyse all market data before making a decision, and the process of making a choice is described as a continuous and interactive activity. This means that retailers need to think about the overall process instead of just focusing on the results of what customers choose (Marceda, et al., 2020). When making decisions about online shopping, credibility is essential by making the organisation clear and easy to understand. In addition to giving details, companies that do business with customers online must show that they are trustworthy and honest. Researchers and practitioners figure out how to use psychographic data to model how consumers decide what to buy and how new things happen in markets. This issue involves research in psychology, economics, sociology, and marketing, similar to research on the agent-based simulation of social systems. Because of this, the new agent concept in artificial intelligence has raised many hopes for dealing with the product return problem (Zhang, 2007).

The return policies affect customer’s decision-making and behaviours. The consumer plays a vital role in the purchase and returns procedures. Consequently, sociological and psychometric aspects influencing and explaining consumer behaviour are crucial in formulating policy and gaining management insights. Therefore, the reliability and applicability of research in this field require a solid empirical base. The thorough study will demonstrate that virtually little empirical evidence exists about customer behaviour and return policies (Rokonuzzaman, et al., 2021). This review focuses on decision-making related to return policies and consumer behaviour in response to such decision-making as shown in figure 2. (Abdulla, et al., 2019). As this paper will demonstrate, customer return research analyses various managerial concerns. The return policy establishes restocking costs, return time limits, channel restrictions, and other elements (Confente, et al., 2021). In addition, operational planning and execution activities influence or are influenced by return policy decisions. Research on consumer returns entails the management of the returned products, including their acquisition, processing, and disposition.

Additionally, return policies affect consumer views and behaviours. The consumer plays a vital role in the purchase and returns procedures. Consequently, sociological and psychometric aspects that influence and explain consumer behaviour play a crucial role in formulating policy and gaining management insights. Thus, the reliability and applicability of research in this field require a solid empirical base.

Customers can evaluate a return policy based on how convenient it is for them to evaluate products, how difficult it will be for them to make potential returns, and how much they will learn from using the product during the allotted time for returns. Various circumstances can cause returns, including unpredictability regarding product valuation and fit, flaws and opportunistic behaviour, amongst other possibilities. Even before the transaction is made, a shop's return policy can discernibly impact customers' behaviour. More than 70% of people who shop online consider the store's return policy before making purchases. As shown in figure 3, return policy (RP), consumer behaviour (CB), planning and execution (PE), and return management (RM) are the four broad and interrelated topics of research that arise collectively from both the customer and retailer perspectives (Abdulla, et al., 2019).

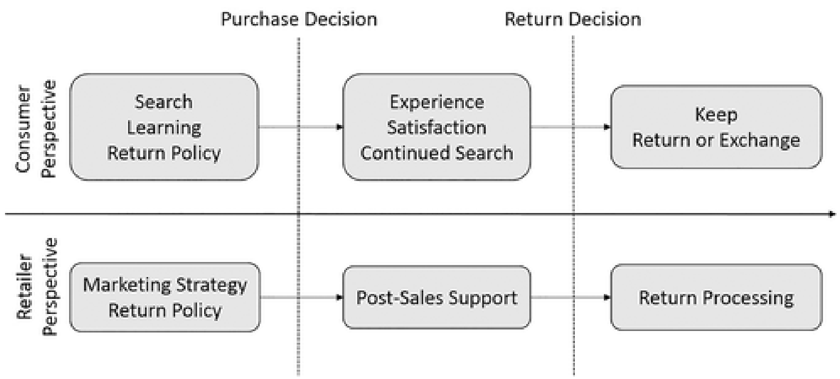

Figure 2: Anatomy of a purchase and return transaction by (Abdulla, et al., 2019).

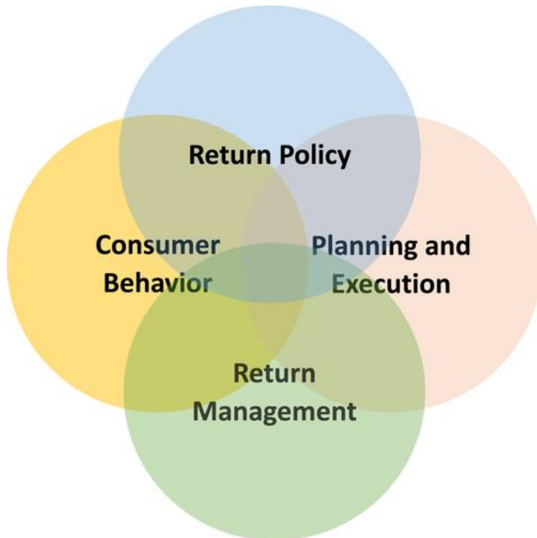

Figure 3: Conceptual framework by (Abdulla, et al., 2019).

2.3 Agent-Based Modelling

Agent-Based modelling is a relatively new method compared to other simulation models because it has an academic area particularly. Three primary components apply the agent-based model: First, the desire to obtain greater insight into systems not effectively captured by conventional approaches. Second, technological advancements in modelling are made feasible, such as Statecharts. Finally, the rapid increase in CPU power and memory results from Agent-Based models being more demanding than other models (Tram, 2022).

Agent-Based Modelling was an academic discipline until the 21st century when a rise in computer processing power made it commercially useful for tackling large-scale corporate problems. In addition, compared to other modelling methodologies, its application is expanding the quickest. Agent-Based Modelling employs a bottom-up method in which the system is depicted as a collection of interacting objects with their behaviours. The system's behaviour derives from the total actions of its agents. Agent-based models can range from a high level of specificity, where agents represent natural objects, to a high level of abstraction, where agents represent competing projects or assets. Population, pedestrian, road traffic, and epidemiological modelling are among the disciplines in which Agent-Based Modelling is particularly helpful for problem-solving (Crooks and Heppenstall, 2012). In reality, however, Agent-Based Modelling is used to model practically anything, from markets to supply chains and logistics, whenever it is necessary to concentrate on particular objects and characterise their local behaviour and relationships.

AnyLogic has developed into an industrial-grade solution with a wide range of applications, including markets and competition, healthcare, manufacturing, retail, social and Ecosystem Dynamics, protection, pedestrian dynamics and road traffic, aerospace, supply chains and logistics, business processes, and project management (Büth, et al., 2017). Even though Agent-

Based Modelling is now incorporated into various commercial solutions for practitioners, AnyLogic remains the market leader in consulting, banking, automotive, telecom, transportation, and government industries.

AnyLogic was created by individuals with a background in distributed systems, concurrency theory, and computer science, as opposed to simulation modellers. Consequently, none of the traditional simulation modelling paradigms was used as a basis. Instead, they implemented software engineering-specific methodologies and languages built to handle complexity. It was discovered that stock-and-flow diagrams and flowcharts are readily described in the object-oriented core language of AnyLogic. There is a great deal of extra value even for the traditional modelling styles: compact structured representation, flexible data specification, etc. The most intriguing feature, however, is the capacity to assemble industrial-strength Agent-Based models in the same visual environment swiftly. In addition, AnyLogic provides ready-to-use constructs for defining agent behaviour, communication, and environment models, as well as robust visualisation features (Borshchev and Filippov, 2004).

2.3.1 Modelling in AnyLogic

Schieritz and Milling (2003) point out academics continue to dispute the characteristics an "agent" might possess: proactive and reactive attributes, spatial awareness, the capacity to learn, social ability, "intelligence," etc. In truth, all agents may be found in applied Agent-Based Modelling: some interact while others live in complete isolation, and some live in space. In contrast, others exist without one, and some learn and adapt while others do not alter their behaviour patterns. Anything, not just humans, can be an agent, including a vehicle, piece of equipment, project, organisation, or investment. Agents don't have to be cognitive or active; they can also be passive objects such as a piece of equipment. Although this may seem counterintuitive, applied Agent-Based Modelling can effectively associate additional properties with the object, such as costs, maintenance, replacement schedules, and breakdown events. Lastly, there are Agent-Based models in which agents do not interact with one another, as in health economics, where individual dynamics depend solely on personal attributes and the surrounding environment (De Marchi and Page, 2014).

Agents are the crucial building components of the AnyLogic design, but in practice, they differ little from simple object-oriented programming classes. In reality, AnyLogic is based on the Java programming language. Still, an intuitive user interface makes it possible to skip writing lengthy blocks of code and instead fill in pre-formatted boxes with the necessary information. Creating a good model does not require expert software development abilities. Still, small operations such as parameter initialisation, messages between agents, and agent movement are specified by adding a few lines of code scripts. A typical AnyLogic Agent-Based model would comprise at least two agent types: The primary type for an environment-representing top-level object and another agent type embedded within the Main (Crooks and Heppenstall, 2012).

Agent-Based Modelling is an individual-centred approach to model construction. When developing an Agent-Based model, the modeller identifies the agents and their parameters, specifies their behaviour using statecharts and events, sets the agents in an environment, creates any necessary connections, and runs the simulation. The system-level behaviour originates from the interplay of numerous individual behaviours. Statecharts are one of the most effective and widely used Agent-Based Modelling tools, allowing users to define the behaviour of an object as a series of states. In contrast, events permit the execution of actions in a model based on time conditions or conditional triggers. Since each agent in the environment is a distinct entity that operates autonomously, agents communicate with each other by sending messages (Borshchev and Filippov, 2004).

Statecharts (shown in figure 4) are the primary tool for modelling agents in AnyLogic, as they are one of the most sophisticated constructs for defining time-based and conditional behaviour. As previously mentioned for agents, statecharts are an adaptation of UML state machines that reduce the tight definition of computer science in favour of a broader emphasis on practical applications. The statechart entry point identifies the first state and provides the statechart with its name. An agent may have numerous statecharts. However, it can include primary states in composite states, which can have a hierarchical structure and be included in other higher-level composite states. Since an agent must always be in a single state, entering a composite state requires an initial state pointer; it can also use history state to indicate the most recently visited state within a composite state. When entering or exiting simple or composite states, it may take action if the guard, known as guard-after-trigger, is evaluated as false.

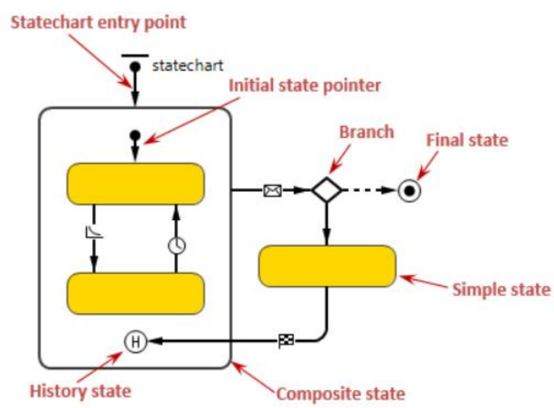

Figure 4: The statecharts by (AnyLogic, 2022).

For a new set of transitions to become active, transitions define how an agent changes its state. A transition can be triggered by a variety of types of events as below.

• Timeout: Specified interval of time measured from when the statechart enters the natural state. Often used to model delays, as shown in figure 5.

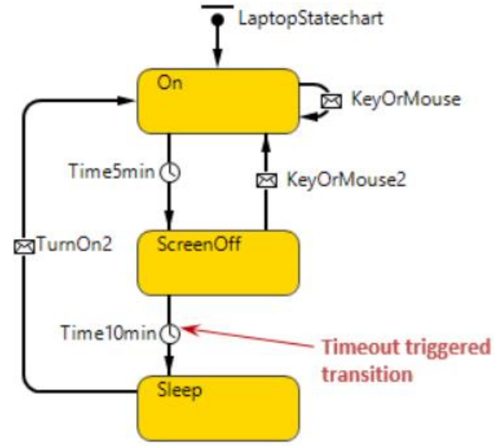

Figure 5: Timeout triggered transition by (AnyLogic, 2022).

• Rate: Similar to timeout, the time interval is selected from an exponential distribution using the supplied rate as a parameter, as shown in figure 6.

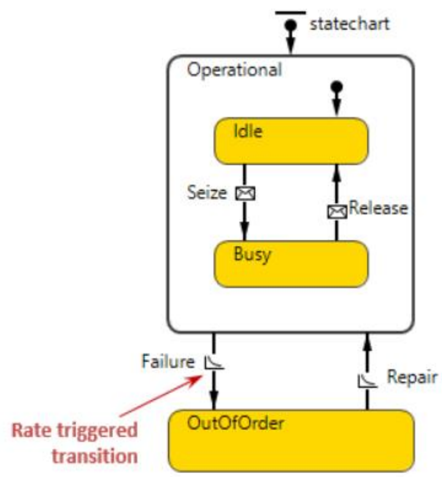

Figure 6: Rate triggered transition by (AnyLogic, 2022).

• Condition: Observe a specified condition and respond when it is true. The condition is an arbitrary boolean statement that may depend on the states of any agents with continuous or discrete dynamics in the entire model, as shown in figure 7.

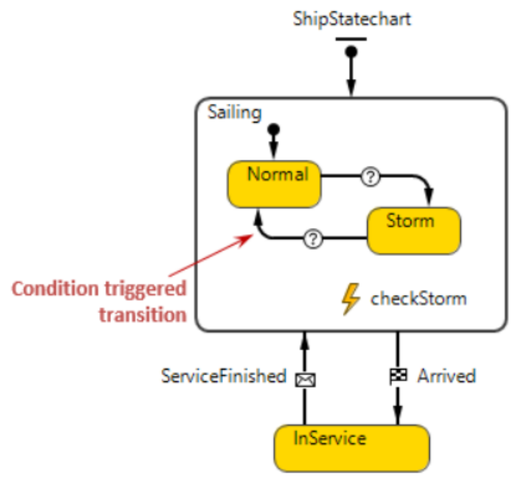

Figure 7: Condition triggered transition by (AnyLogic, 2022).

• Message: When the statechart or agent receives a message from the outside. Agents can provide a message template in the transition's properties, and only a message-matching condition will trigger the transition, as shown in figure 8.

• Arrival: used only for a moving agent when the item arrives at the specific area, as shown in figure 9.

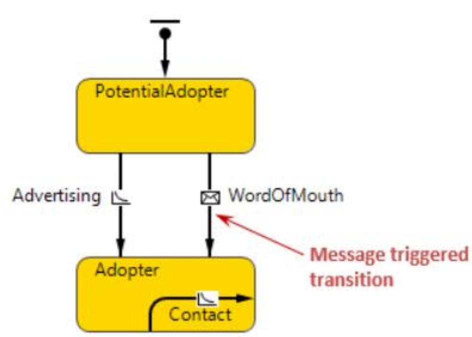

Figure 8: Message triggered transition by (AnyLogic, 2022).

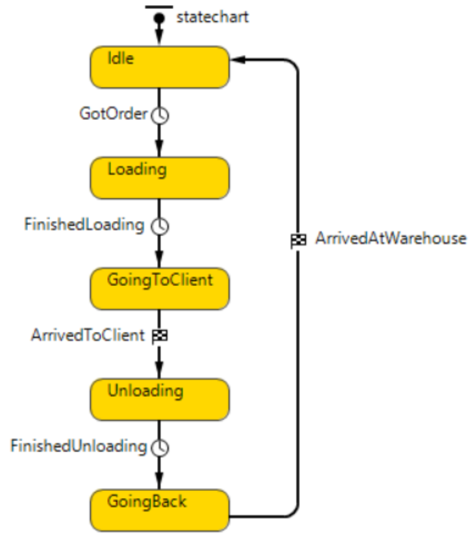

Figure 9: Arrival triggered transition by (AnyLogic, 2022).

2.3.2 Verification and validation of simulation model

Before they make a decision based on the model, stakeholders will require assurance that the ABM used as a decision-support tool is valid. Therefore, the distinction between verification and validation is made. Verification examines the accuracy of a computer simulation model in relation to its conceptual model. The goal is to verify that a conceptual model has been correctly implemented in the computer simulation model. It is comparable to finding and correcting programming errors. AnyLogic and other visual interactive simulation tools provide debugging functionality for model validation. For library-based tools, they can use unit testing tools (Onggo and Karatas, 2016).

Model validation aims to ensure that a simulation model is suitable for its intended purpose by comparing its output to the expected result. For example, empirical data or analytic/theoretical models may predict the desired outcome (Sargent, 2013). Given that both DES and ABMS are typically used to represent stochastic dynamic systems and must track the entities or agents during simulation, the validation techniques commonly employed in DES also apply to ABMS. Face validation, operational validation, white-box validation, and black-box validation are the validation techniques. Sargent (2013) provides a useful tutorial on validation techniques applicable to ABMS.

Nevertheless, model validation in ABMS is particularly challenging. First, ABMs must be validated on multiple levels (agent level, system level and, possibly, some intermediate levels). A second difficulty arises from the need to represent behaviour in ABM using rules or algorithms frequently. Therefore, we must determine if the practices utilised in our ABM accurately represent the rules operated by actual agents. The heterogeneity of the agents exacerbates the difficulty of this issue. Lastly, an ABM frequently necessitates high-precision data, which are not always available (Onggo and Karatas, 2016).

Consequently, empirical data validation may not always be possible. Given these obstacles, research is required to develop validation techniques and tools for ABMS. However, when ABMS is used for decision-making, these tools can increase the confidence of stakeholders.

The increasing use of ABMS to explain social phenomena or systems with emergent behaviour requires us to investigate the unknown agent-level mechanisms/behaviours to describe a known population-level behaviour. However, as stated previously, this method employs abductive logic. Consequently, empirical validation is almost impossible in this circumstance (Kunc, et al., 2019).

2.4 Empirical studies of Agent-Based model simulation (ABMS) about consumer decision-making

Agent-based model simulation (ABMS) simulates complex systems and comprises autonomous agents interacting with each other. ABMS certainly have far-reaching consequences for corporations utilising computers to support decision-making (Smith and Conrey, 2007). Because the agents in an agent-based system communicate with each other and their environment, the ABMS methodology could solve distributed and complicated issues. For agent-based techniques, it is easier to find a solution because the problem is split down into more minor matters. The agents interact with their environment, are capable of making independent decisions, and reduce the complexity of issues. (Macal and North, 2005). Moreover, the adaptability of ABMS is simple to add or delete agents from a dynamic system. We can use agent-based techniques in many different ways because it is easy to remove or add agents as needed during the study (Roozmand, et al., 2011).

A review of the Agent-based model simulation (ABMS) literature about consumer decision-making processes: Roozmand, et al. (2011) indicates that ABMS helps explain when and why a customer purchases a specific product. They considered two demands connected to the car-buying scenario and the influence of culture, personality, personal attributes, and the social setting to determine whether a customer is motivated to make a purchase decision. The stages of consumer behaviour are the need of the customer, information search, alternative evaluation, purchase, and post-purchase activities. The customer decision process begins with identifying demand (Max-Neef, 2017). Other essential concepts at this level are the actual state, the target state, and the tolerance threshold for each customer requirement. Actual state refers to the level of consumer satisfaction with the product at present. The target state is the satisfaction of the consumer. A customer only feels a need when the difference between the intended and actual condition exceeds the target state's tolerance threshold, compelling the consumer to take action to satisfy the requirement (Roozmand, et al., 2011). Then, the consumer decision-making process's search, evaluation, and selection phases come into action. The Conceptual model for consumer agents as shown in figure 4.

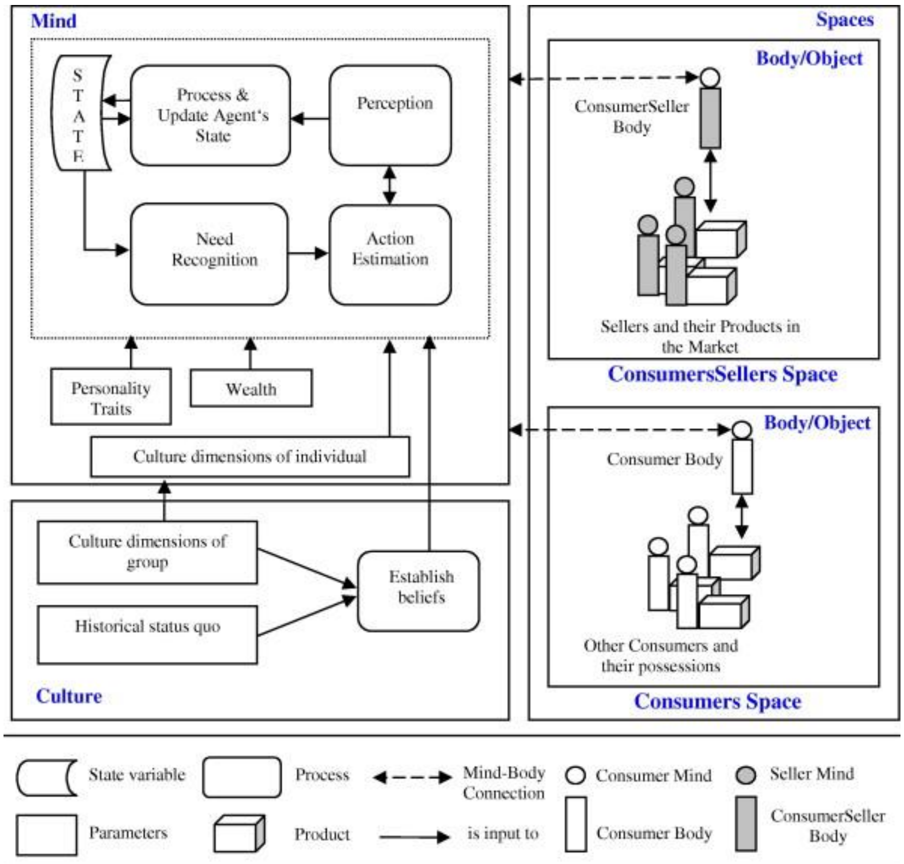

Figure 10: Conceptual model for consumer decision making process by (Roozmand, et al., 2011).

Furthermore, many researchers used simulations to study customer decision-making. McHugh, et al. (2016) pointed out using ABMS to test decision-making in collective leadership and intelligence. Furthermore, there is some correlation between the outcomes of the agent-based simulation. Thus, a basis for studying collective-level decision-making is fundamentally collaborative leadership. Research can examine leadership and decision-making in many forms of collectives.

Namany, et al. (2020) implement a dynamic decision-making framework that simulates perishable food market strategies under different food security conditions dependent on the availability of food on a continuous and regular basis. However, food markets, which are supplied by both local production and foreign trade, are subject to risks arising from unanticipated supply chain disruptions, commodity price volatility, and other unforeseen events such as natural catastrophes. To offset the threats to the stability of food systems, the food sector's decision-making should be strengthened and made more robust to account for any changes that could lead to food shortages.

Bozdoğan, et al. (2022) formulated the modelling of the design of a dynamic closed-loop supply chain network. In most cases, the supply chain network comprises all the links that allow products to move from suppliers to manufacturers, distribution centres, and customers. For example, a product could go back into the supply chain after being shipped to a customer if it has reached its end of life or end of use, if it is still under warranty, or if it was sent to the wrong address or is broken. After sorting and inspecting, a decision is made to use one of the reverse logistics options, such as repairing, remanufacturing, refurbishing, or recycling, depending on the quality of the returned product and the technical and economic possibilities (Utomo, et al., 2018). As shown in figure 4, CLSC is the name for systems that handle both forward and backward flows as a whole, formulated the modelling of the design of a dynamic closed-loop supply chain network (Coenen, et al., 2018). The CLSC networks include both forward and reverse flow at the same time. Forward flow begins with the purchase of raw materials or parts from suppliers and terminates with the delivery of items to customers. The reverse flow starts when raw materials and or parts are returned to suppliers. The customer is not only the end of the forward flow but also the beginning of the backward flow (Abdallah and El-Beheiry, 2022). The first step in reverse logistics is the collection of products from consumers that have reached their end of life or end of use at collection facilities. The treatment of the returned products and their subsequent reintegration into the forward network or their disposal in landfills marks the conclusion of the reverse flow, as shown in figure 5. Thus, the nature of the supply chain, the ABM technique has proven to be successful in handling dynamic structures, individual goals, and behaviours inside the model. This makes the technique appropriate. The proposed model is notably helpful in addressing the issues that arise when modelling supply chain networks that incorporate reverse flow. These networks are more complex than networks that just involve forward movement. The proposed method offers businesses the opportunity for network administration that is not only easily understood but also highly visual, and effective in accurately portraying reality (Bozdoğan, et al., 2022).

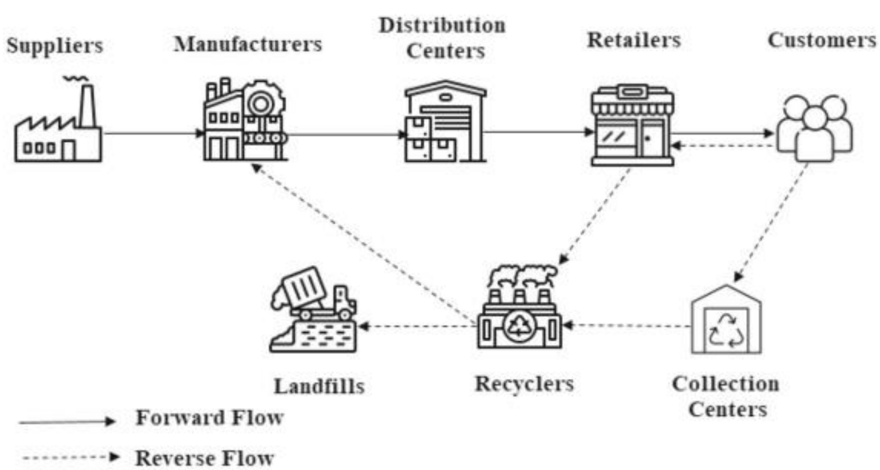

Figure 11: A closed-loop supply chain network for recycling by (Bozdoğan, et al., 2022).

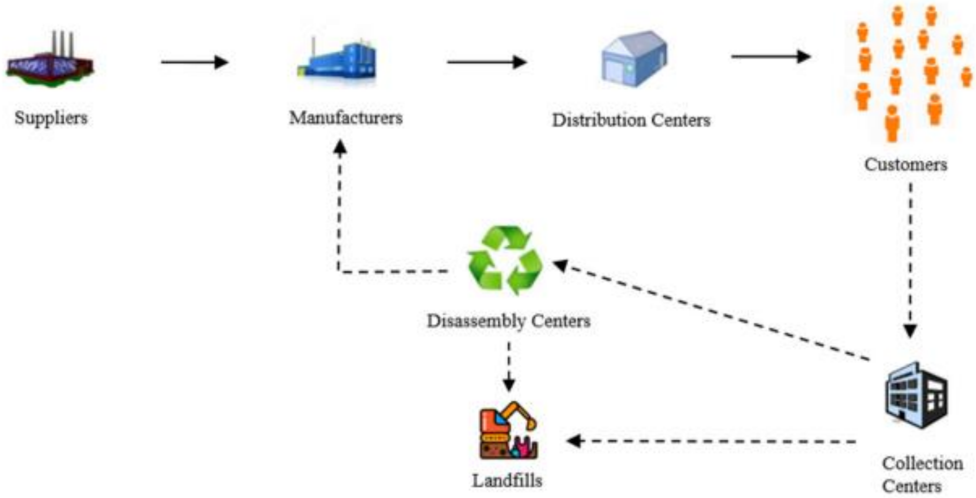

Figure 12: The structure of proposed closed-loop supply chain network by (Bozdoğan, et al., 2022).

So, the focus of this dissertation is on using agent-based model simulation to describe how customers make decisions about returning products. This project is unique because it uses the ABMS to simulate how customers make decisions about returning apparel products from an omnichannel. It will be discussed in further detail in the chapter which will follow.

CHAPTER 3. METHODOLOGY

This chapter describes the step in building the model of customer decision-making about product return—first, analysis of the existing data from the product return in a COVID-19 consumer behaviour survey. Next, create a flowchart diagram to understand consumer decision-making about product return and build an agent-based model simulation; the model will be implemented using AnyLogic 8.7.7 simulation software to simulate the model and gather the result for deeper analysis.

3.1 Data analysis and insight from existing survey.

From a survey on product return in COVID-19 consumer behaviour (The original survey was approved under Ergo authorisation 64302). This survey raises many questions related to the return of products. For example, which is the reason fashion-purchasing circumstances might make you soon regret your purchase and are more likely to return the items? How many fashion items bought have you returned? What are your frequent reasons for returning fashion items you purchased online? In addition, from a customer perspective, this questionnaire has the customer conditions in many aspects, including gender, income and education level. All of which affect the decision of the consumer to return the product. Therefore, it is important to begin analysing this survey that we created a framework for answering research questions that would explain the research question or objective of this project to consumer decision-making in product return. We can choose to consider some of the questions that are important or influence the consumer's decision to return a product. The questions that we selected for consideration were as follows. First, the question is whether customers have regretted their purchase and the trend to return the items. This question is interesting because the reasons for regret after placing an order differ for each individual. By the proportion of people who regret their purchase compared to those who feel confident about their purchase, it is 27.1% and 72.9%, respectively, as shown in figure 13. Emotion can be a significant factor in decision-making. However, it is more frequently ignored than thoroughly considered. Gains and losses that can be physically viewed and quantitatively calculated can be used to interpret consumer behaviour. It is also true and vital to highlight that emotions influence consumers' decision-making processes they experience before, during, and after the occurrence of negative outcomes. Some consumers may prioritise the reduction of unpleasant feelings such as discontentment, frustration, and regret. In order to evaluate how cognitive effort and justification jointly influence negative emotions, the primary negative emotion of interest in the current study was post-purchase regret. Regret was selected as the emotion of interest for multiple reasons: It has relatively distinct cognitive characteristics, The justification of a decision influences it, It is affected by cognitive effort (Park, et al., 2015).

Justification is essential to consumer decision-making. The rationalisation involved in justification can reduce decision conflict and enable individuals to develop reasons to justify a challenging choice (Shafir, et al., 1993). Explaining a choice is, therefore, a frequent activity, and customers are incentivised to maximise justification. Justification objectives can shape customers' choice paths and assist them in sensible resource allocation, such as cognitive effort or money. In addition to rationale, the cognitive effort is equally valuable to consumers. Exerting mental effort increases a decision's confidence and precision. Despite the fact that justification and cognitive effort exertion are distinct and independent decision-making entities, the customer can expend the mental effort to justify a decision and reduce post-decision discomfort. However, this is only likely if the information requested is advantageous to the decision. This suggests that affliction following a decision may arise if cognitive effort or rationale is squandered (Park and Hill, 2018). The reason for regret arising after the purchase in this survey is due to misreading the product description or the moment of unstable mood before decision-making. Other reasons have a similar effect.

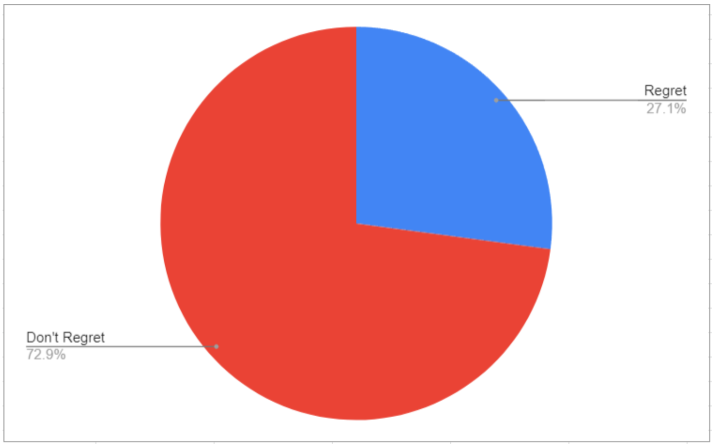

Figure 13: The pie chart of people who regret their purchase compared to those who do not regret.

From the analysis of the results of the return, after the customer has received the product, the decision-making analysis of the customer can be divided into three main reasons:

1. intentional/willful the order to return the mass of products and keep only the piece with which the customer is satisfied. Since the retailer cannot fully resolve size and preference uncertainties without physically interacting with the item, several online clothes shops have decided to provide free returns, allowing buyers to assess the product at home prior to making a final purchase choice. In other words, free returns enable consumers to order clothing, try it on, and return it without paying a fee. This technique is referred to as bracketing in the retail business, and its effects on retailers are the primary topic of this study. a lot of customers will bracket at least some of their online purchases (Park and Hill, 2018).

2. It is required to return the product due to its conditio. Sometimes customers are disappointed when they receive a product because of its size, colour, texture or design, and stores allow customers to return items after they evaluate the item and decide whether or not to keep it.

3. Do not want to return the product. Some customers do not want the return process unless the product is too damaged to be accepted compared to the two cases mentioned above. This group of customers has a higher acceptance rate in terms of size, colour or design. They try to accept flaws or things that don't meet their expectations. This customer group may include customers with significant online purchasing expertise; they have techniques for selecting the best and most appropriate products. They are able to recognize the correct size and compare the colours in the photographs to the actual product. They are able to comprehend the details of the product in the description, such as the sewing pattern, the material used, the composition of the goods, etc., which reduces their likelihood of returning the item. Because they carefully consider the selection of products. as shown in figure 14.

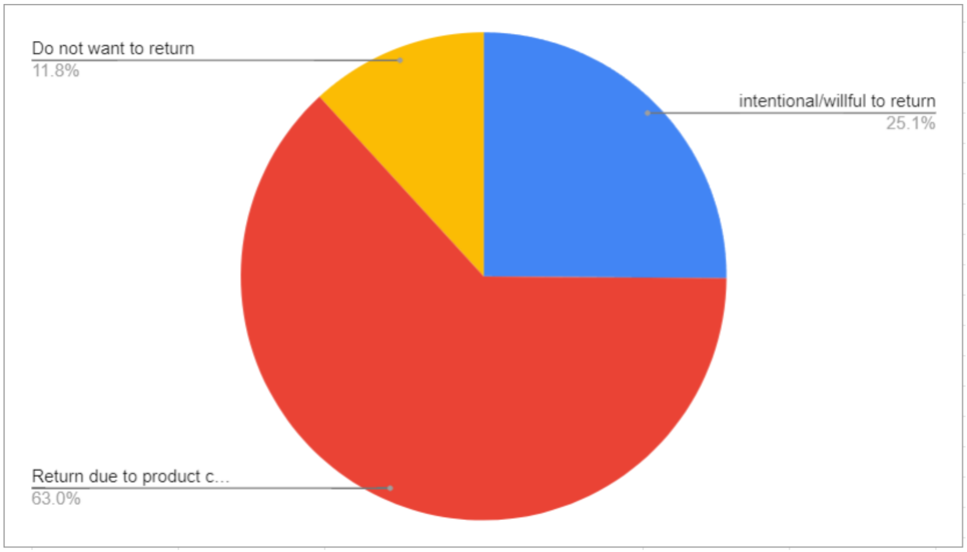

Figure 14: The pie chart of reasons for returning items in terms of customer decision-making.

Other information relevant to modelling is the return model, either a store return or a manual return as shown in figure 15. Although many shops desire to implement the buy online and pick up in-store (BOPS) or BORP as mentioned on chapter 2.1, after COVID-19, consumers' lifestyles or norms shifted to the more involved online channel. For BOPS, customers can purchase products online and return unsatisfied items to the store. This technique combines the benefits of both online and physical channels by allowing consumers to return things at a convenient location and time and to receive prompt payment for returned items. This can enhance consumer convenience, contentment, and loyalty, affecting their perceptions and purchasing inclinations. According to a UPS survey, 82% of online shoppers will complete their purchases if offered a free return service (UPS, 2015).

Moreover, applying the BORS strategy will undoubtedly result in increased shop visits, which can help brick-and-mortar stores create extra opportunities for cross-selling activities and improve profitability, either through impulse purchases or with the support of store staff. Around 25% of consumers who visit physical stores to return defective merchandise also make additional purchases (UPS, 2016).

The self-return section could be described as the customer receiving a return form sent with the product or online when customers press a return request in some stores. Online offers consumers the option to choose either a shipping company or to schedule a time for a carrier to pick up the items at the customer's address. By the way, it is mostly a free return. However, suppose the store does not provide a return form with the product. In that case, if the customer requests a return, the store will guide the delivery process or Alternative shipping companies to the customer. Still, the customer has to do it all by himself, and the cost may depend on the return, whether it is a return due to the shop's error or a return due to the customer's decision. This will affect the cost of returning the product.

Additional information includes other reasons relevant to the decision to return the product. Interesting is the reason for finding better product options, whether in terms of promotions, prices, designs or stores. Furthermore, the survey also reveals how fewer customers decide to return, which is mainly consistent with why customers return the items above and how stricter policies influence their purchase decisions. And return the product as well.

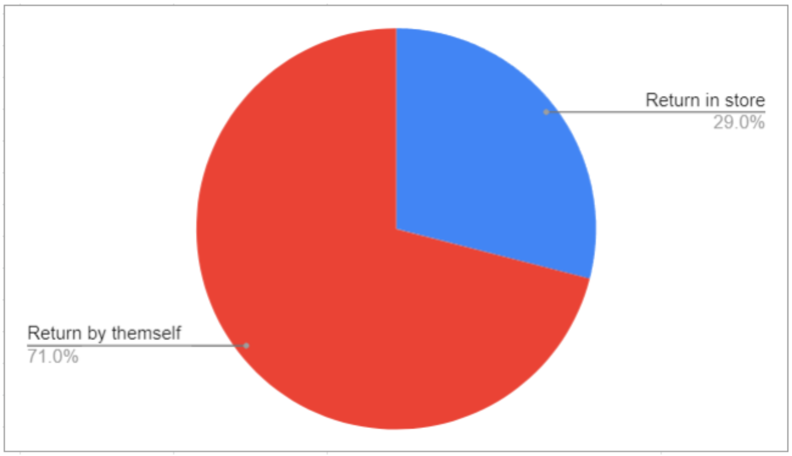

Figure 15: The pie chart of the way to return.

3.2 Design customer's decision-making about product return by flowchart diagram

In Chapter 2.1.1, The process of product return, Frei, et al. (2022) points out that the process begins with the consumer purchasing a product in-store or online for home delivery, parcel shop delivery, or Click and Collect. Therefore, it increases the likelihood that the consumer may refuse delivery or not pick up the order. Suppose the customer receives the item and decides to return it. There are multiple entry points to the returns process. The customers can return the item or call customer service and be offered a refund without returning the product.

Products returned to a store may take various exit routes: the return may be refused, and the customer will keep the item; The retailers may discard the item; they may donate it to charity; they may recycle it; they may return it to the manufacturer/supplier; it may be kept in store to be resold at full or discounted price, or the store may send it to the Return Centre (RC). Rarely do shop staff organise local transportation to a neighbouring store that sells the goods, requires and carries them in stock. The process continues with the product's arrival at the return centre, where its barcode is scanned and inspected. There is a slight possibility that a return will be denied. In this case, the client is notified, and the product is returned. The return code is recorded, and a refund is delivered if the return is approved (Frei, et al., 2022).

We could adapt the return process regarding supply chain management in terms of customer decision-making about product return. We use flow diagrams as a framework and scope to create a model to describe consumer decisions or behaviour when deciding to return the product, as shown in figure 16.

At the starting point of the flowchart, after the consumer has completed the purchase order, as shown in the state of "customer places an order online". The first decision is made immediately after the order has been completed and payment has been made. The decision was to change their mind about placing an order in the state of "Change of mind". Some customers who had just placed an order later decided they no longer desired the product and cancelled their orders in the state of "Decide to cancel order". This decision is made between the customer waiting to receive the product and the order cancellation. Despite the fact many stores have proposed strategies for reducing post-purchase regret, consumers continue to be caught in this sticky situation. For example, there are instances in which post-purchase regrets were not the result of a seller's error but rather a consumer's lack of self-control, such as a poor financial decision. In addition, consumers are typically blinded by long-term consequences, such as escalating credit card bills, when they make poor choices (Lazim, et al., 2020).

Customers who regret an order will be in a state of change of mind. Whenever a customer is in this situation, they will do whatever it takes to find a way to cancel the product as quickly as possible. As shown in the state of "Cancel in time or not". However, some companies' orders have a fast-handling system to enter the prepared shipment status. Therefore, they will be in the state of "Order cancelled" if the customer cancels in time when the order goes into the packing process, they have to wait for the delivery as usual, as shown in the state "Can't stop delivery". The customer knows how important it is to cancel unwanted orders on time. Because that means drastically reducing the time taken for their return, and in the state of a "refund process", customers who cancel their order in time will go through the refund process quickly. Indeed, they only wait for the process to complete without any action. And, of course, if cancelled in time, it will get a refund.

Customers who do not regret their orders will be in a state of waiting for products to be delivered as in the state of "Customer waiting order", and the delivery time will depend on the shipping company, delivery options and the distance between the customer's address and the warehouse or store. According to a survey within the UK, the standard for domestic delivery is about 3-5 days at 71% (PostNord, 2020). The state of "Customer received items" will combine customers in a waiting order with customers who change their minds and wish to cancel the order. But they can't cancel the product in time, so they have to wait for the product when the customer has received the item. We will consider who has pre-decided or intentionally ordered multiple items to choose the part they desire and return most of the products or a bracketing purchase behaviour in the state of "Bracketing or not". As mentioned in Chapter 2.1, Makkonen, et al. (2021) noted that consumers with greater online shopping experience may return products more frequently, even when there is nothing wrong with the product. They may engage in bracketing, ordering multiple homogeneous products to keep only a small proportion as shown in the state of " select the desired product " and return the remainder. Customers who intentionally ordered bracketing must be classified to consider the customer in case of wanting to return the product from the actual product.

After the customer has received the product, the customer will consider the product in many aspects by trying the product. In this state, we try to focus on the customer's decision in the aspect of trying the product in the state of "Customer decides to return item". We split off customers who want to cancel their orders before they are delivered. We separate customers who have intentionally returned the product. Although this includes customers who initially intend to cancel the product but cannot cancel in time, however, they have the opportunity to keep the product because they are satisfied with the product when they have tried the product, making this decision analysis.

It could specify which of the remaining reasons will affect the decision to return an item in this state, which is mentioned in Chapter 2.1. The decision to return an item in this state includes wrongly sized or poor fit due to the store's size guide not meeting every brand's product; there is a chance that the measure may not fit when the customer receives the product and tries it. In addition, in terms of designing clothes in styles such as oversized, medium fit, loose fit, or large fit etc., people have different personalities in different body parts, which is why this impacts the return of products.

Mismatched product information means when the customer receives the item. Still, the condition does not match the store's description, which in most cases is caused by the store's mistake in creating the product description. Because product descriptions are important, they will affect customer decision-making. For example, The description states that this shirt has two pockets, but upon receipt of the item, the customer found that there was only one pocket. Jin, et al. (2020) demonstrates that even with full refunds, a money-back guarantee policy can increase profits by increasing sales volume and allowing retailers to charge a price premium that customers are willing to pay for a reduced risk of product mismatch. This is why customers often return an item when they feel it doesn't match the product description or the image shown for advertising. Because the product description or information is critical in their purchasing decision, it is also important when making a return decision.

Faulty or damaged product, that is, the product is damaged, damaged or deformed from normal conditions, mainly due to the fault of the quality control department, and some may damage the product due to transportation. Therefore, the customer must return the defective product, which is unacceptable, especially for high-priced products; product quality control is crucial. Mismatched needs, desires, or expectations directly impact customer decisions, as each customer has different expectations for the product. This is more difficult for the store to control than other reasons. For example, some people imagine the product's look compared to themselves and expect it to look good. Still, upon receiving the product, the product's design may sometimes contain details that do not match the customer's expectations. As a result, they don't like the product and feel it is no longer required. Consumer satisfaction is the focus of the investigation. It is the degree to which consumers' perceptions of their online shopping experience correspond to their expectations. Before engaging in online shopping, most consumers form expectations regarding the website's product, vendor, service, and quality. These expectations influence their attitudes and intentions to shop at a particular online store and their subsequent decision-making and purchasing behaviour. Customers achieve a high level of satisfaction if their expectations are met, which positively influences their attitudes, intentions, decisions, and purchasing behaviour (Li and Zhang, 2002). These are largely consistent with the causes identified in prior research. In addition, we noticed that those who returned products more frequently were more likely to cite a mismatch with needs, wants, or preferences. In contrast, those who returned products less frequently were more likely to explain a faulty or damaged product (Makkonen, et al., 2021).

When the customer decides to return the product in the state of "Customer request to return". The customer submits a return request to the retailer by stating their return request via the app, email or phone whether to return the self or return to the store; after the customer sends the item for return to the store. This is the final discretion regarding the consumer's decision; after that will be at the discretion. Then, evaluate according to the store's policy whether the store can refund the returned product to the customer or not. And if the product violates the store's return policy, it is necessary to return the product to the consumer. And if the returned product complies with the company's terms and policies, the customer will be in the waiting period for a refund and finally receive a refund.

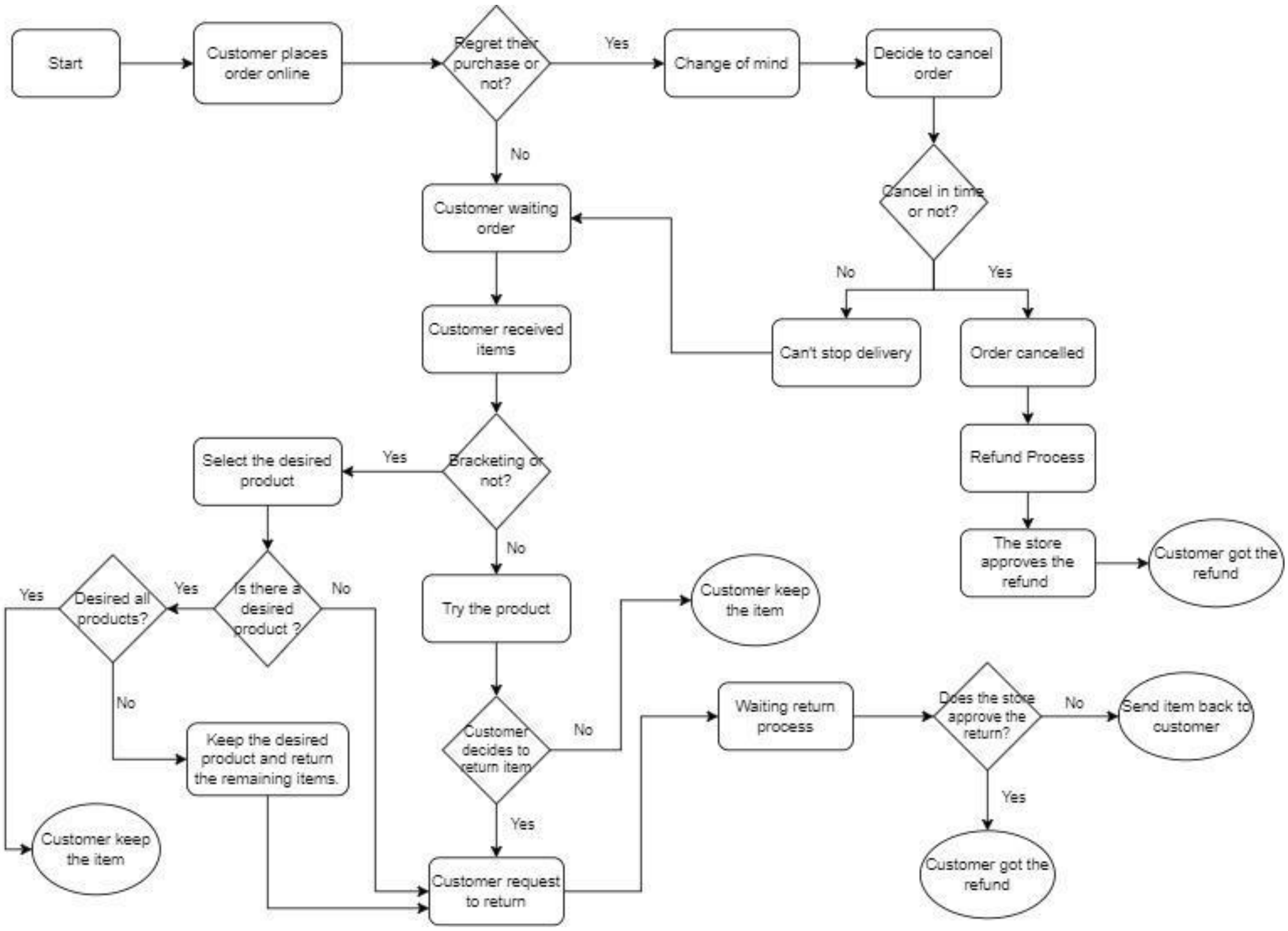

Figure 16: The flowchart diagram of customer decision-making about product returns

3.3 Developing agent-based model to describe customer decision-making about product return

Why do we need simulation in business decision-making? Because some problems in the real world can be expensive and, in some cases, dangerous. It can be unethical or downright illegal. It is undoubtedly true that the simulation model is a simplification of the real world. We should not make a seamless model that is as complex as the real world because otherwise, if we cannot solve a complex real-world problem directly, how can we solve a model that is as complex as the real world? A model needs to be representative of the real world that is being modelled. The Agent-based model simulation must capture the key agent, the key behaviours, and the essential elements of the system (Onggo and Foramitti, 2021). Specifically, this research aims/ research question to describe the consumer's decision to return the product. Therefore, the Agent-based model simulation is very suitable for achieving this purpose.

Agent-based model simulation (ABMS) is helpful for the analysis of complex adaptive systems and emergent phenomena in the social sciences, engineering, biology, and other disciplines. Situations or states are patterns or global behaviours that cannot be deduced from the properties of their constituents. Consequently, an emergent structure or behaviour is generated by interacting entities. Agent-based modelling is gaining attention in customer product return decision-making, primarily because it provides a means of incorporating the influence of human decision-making on customer purchasing and returning, taking into account social interaction, policy, reasons, adaptation, and decision-making at various levels. Agent-based models have the potential to simulate individual decision-making entities and their interactions, to integrate social processes and non-monetary impacts on decision-making, and to dynamically link social and environmental processes (Klügl and Bazzan, 2012).

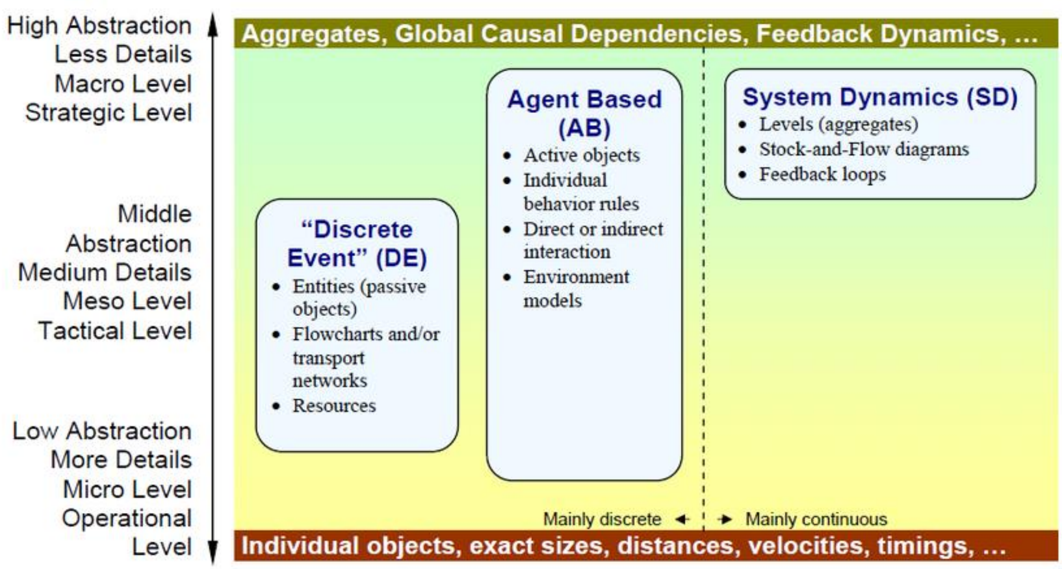

Figure 17: Approaches in simulation modelling on abstraction level scale by (Borshchev, 2013)

Figure 17 shows an agent-Based model, which can range from models in which agents represent physical objects to models in which agents represent entire systems. Choosing the appropriate abstraction level is crucial to the success of a model, and it is customary to reconsider the abstraction level occasionally. In most cases, modellers begin at a high level of abstraction and add details as needed, ignoring anything below the desired level of abstraction. Agent-based applications eliminate the necessity for additional abstractions and assumptions (Borshchev, 2013).

When should ABM approaches be adopted in the context of research? ABM's benefits include:

- Combining social and environmental models.
- Incorporating the influence of micro-level decision-making in environmental management.
- Investigating the emergence of collective reactions to ecological management strategies.

Include the capacity to model decision-making at several levels (such as individuals and organisations) and adaptive behaviour at the individual or system level (Matthews, et. al., 2007).

3.3.1 Agent-based simulation in AnyLogic

To start the Agent-based Model simulation (ABMS), we create a new agent type name “Consumer” as a 2D person in continuous space dimensions 500 x 500 and this is a heterogeneous agent/individual. The time stack chart has updated data automatically and displays up to 60 latest simple and sales in time windows of 60 model time units.The main model is shown in figure 18. Then, design the Statechart for developing the model.The agent-based model simulation starts with the state chart design in the case that we need to define behaviour that some models cannot describe using events and dynamic events. This is possible using state diagrams. Statecharts are the most sophisticated way to depict event- and time-driven behaviour. This event- and time-ordering of operations is so pervasive for some objects that you can best describe their behaviour using a state transition diagram, a Statechart diagram. States and transitions make up a Statechart. Conditions specified by the user can trigger transitions (timeouts or rates, messages received by the Statechart, and Boolean conditions). For example, implementing a transition might result in a state transition in which a new set of transitions become active. States in the Statechart may be hierarchical; that is, they may contain additional states and transitions. Statecharts illustrate the state space of a given algorithm, the occurrences that cause transitions and the subsequent actions. Using statecharts, you can visually represent a richer range of discrete behaviours than those offered by block-based tools, such as idle/busy, open/closed, and up/down (AnyLogic, 2022).

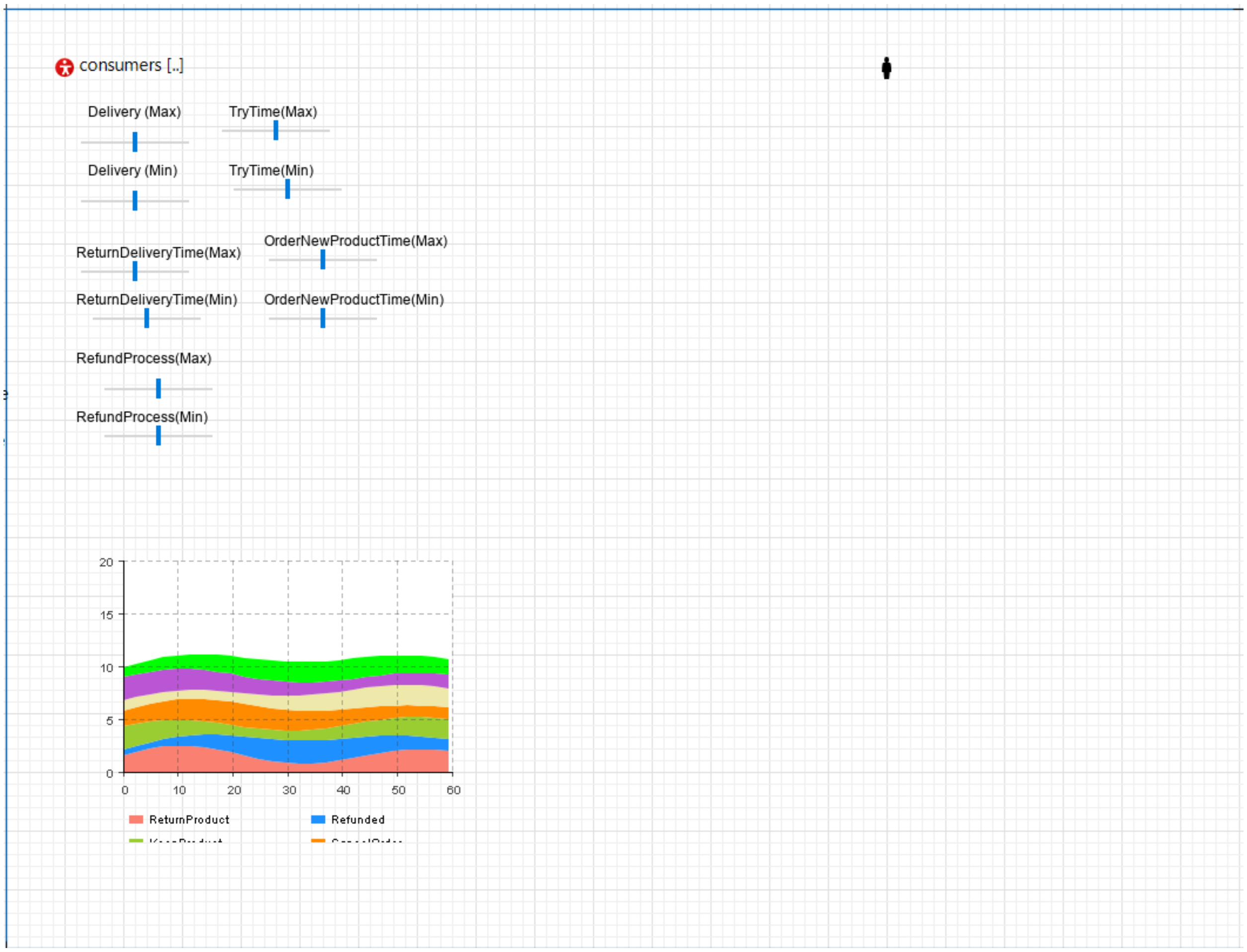

Figure 18: The main setting of model

After we have designed the flowchart diagram of customer decision-making about product returns in Chapter 3.2. We have continuously developed that idea. Lead to Statechart diagram of customer decision-making about product return as shown in figure 19.

The model framework of Agent-based model simulation (ABMS) is to consider the 1000 customers who make purchase decisions in the system as we divide it into consideration. The results are in 90-day intervals. In the transition, use a function uniform with the highest and lowest setting time. There are sliders to adjust the highest and lowest setting times. Different settings are considered in the result, uniform timeout and specific timeouts. The run format is stopped at the specific time and random seed (unique simulation runs). The model setting will show in the appendices. The starting point of the chart is the Statechart entry point, which indicates the chart's initial state. Each Statechart should have a single defined entry point. However, you may define multiple independent Statecharts for a single agent, each describing a distinct process. AnyLogic will determine the number of distinct Statecharts in this scenario by analysing the number of statechart entry points. This Statechart have 12 states as follows;

1. "DecideToPlaceOrder" refers to the state where the customer decides to place an order and completes the payment.

2. "WaitingOrder" refers to the state after the product management system has confirmed the customer's order. The customer will be in a state of waiting for the product to be delivered.

3. "CancellingOrder" refers to a state in which a customer changes their mind, resulting in a decision to cancel the product.

4. "OrderCancelled" refers to the state after the customer has decided to cancel the order and the order is cancelled on time; the customer can cancel that order immediately. (The product has not been packed to prepare for shipping)

5. "CantStopDelivery" refers to the state after the customer decides to cancel the order, but if the order is cancelled beyond the time, the customer cannot cancel the order. (The product is still packed to prepare for shipping)

6. "ProductArrvied" refers to the state after the product has been delivered to the customer's address.

7. "Bracketing" refers to the customer ordering the same product but in different sizes or conditions to try multiple items of the same product.

8. "ReceivingProduct" refers to the state in which a customer considers a product by testing the product or testing certain conditions on the product, such as a Legit check.

9. "KeepProduct" refers to the state where the customer decides not to return or keep the item. In other words, the customer receives a satisfactory or acceptable product. However, In this state, the buyer may decide to place a new order after some time.

10. "ReturnProduct" refers to the state in which the customer decides to return the product. In other words, the customer is not satisfied with the product, or the product does not meet their expectations or requirements. In this state, the buyer may decide to place a new order after some time.

11. "CantReturn" refers to the state in which the customer returns the product to the store but does not meet the standards or return policy. Then, the store sends the item back to the customer again. Consequently, this state is pending for the product to be returned to the consumer.

12. "Refunded" refers to the state in which the customer has received a refund on the return of the product. However, In this state, the buyer may decide to place a new order after some time.

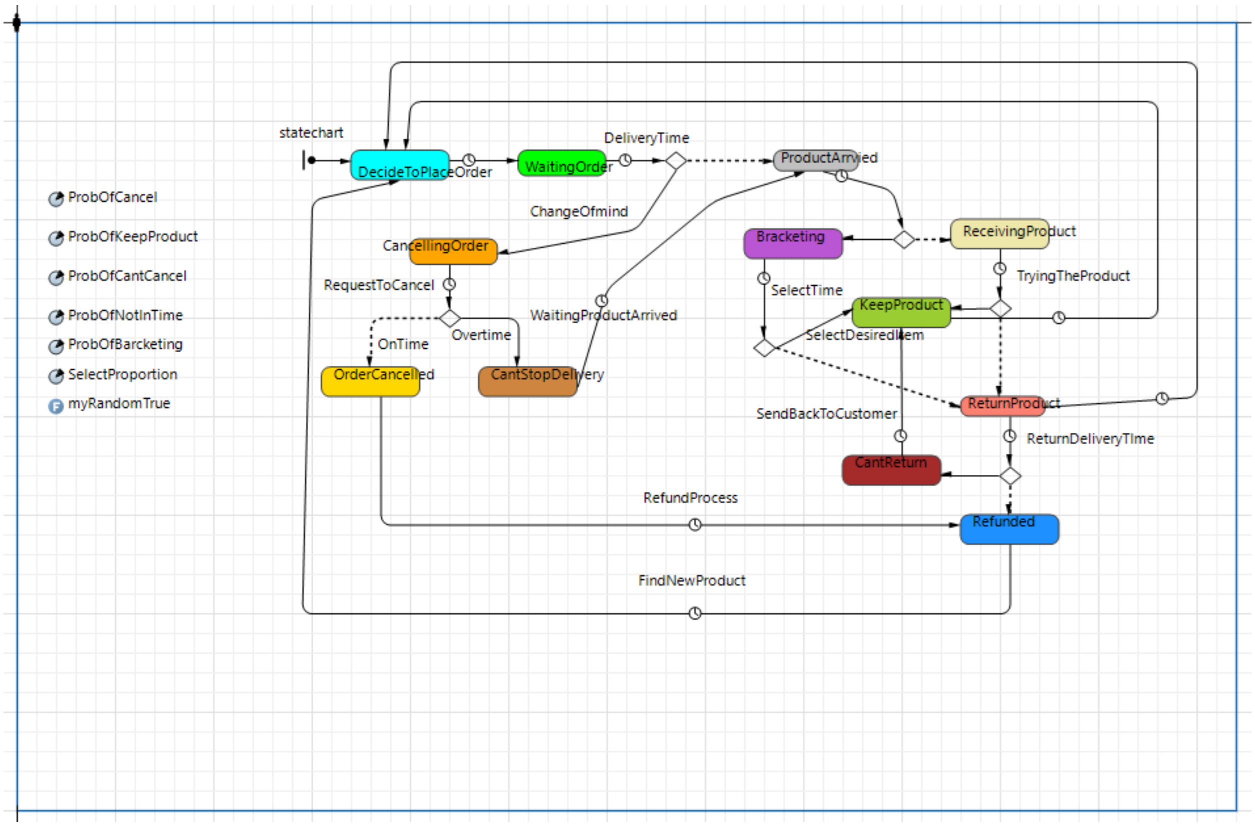

Figure 19: The Statechart of customer decision-making about product return

Table 1. shows the transitions that connect each state in statechart. A transition represents the change from one state to another. A transition indicates that the statechart changes from one state to another and executes the specified action if the specified trigger event occurs and the specified guard condition is met. This is referred to as the transition occurs. The beginning of a transition is located on the boundary of the source state. The conclusion of a transition occurs at the state border of the transition's target state. A transition may traverse both simple and composite state borders freely. If the source of a transition is within a state, and its destination is outside the state. Then the state is considered to have been left by the transition. In the event of such a transition, the exit action of the excited state is executed. If the source of a transition is outside a state and its destination is inside the state. Then the transition is considered to have entered the state. The state's entry action is carried out if such a transition is made. If both the source and destination of a transition are located outside a state, but a portion of the transition lies within the state, this state is neither entered nor exited (Anylogic, 2022). Table 2. Shows the parameters that

are used in each transition. These data are based on a selective survey assessing consumer decision-making and questions. In Time stack chart show the result state in 7 essential states consist of “ReturnProduct", "Refunded", "KeepProduct", "CancelOrder", "ReceivingProduct", "Bracketing", and "WaitingOrder". By setting the variables as shown in Tables 3 and 4.

Table 1: The transitions in the statechart of Agent-based model simulation

Transition	**Triggered by**	**Value**	**Stateconnect**	**Source**
PlaceOrder	Timeout	0.01	1 and 2	Assumed based on product return in a COVID-19 consumer behaviour survey
DeliveryTime	Timeout	uniform(main. MaxDeliveryTime, main.MinDeliveryTime)	2 and (3 or 4)	(Amazon, 2022)
ChangeOfmind	Condition	myRandomTrue (ProbOfCancel)	2 and 3	Assumed based on product return in a COVID-19 consumer behaviour survey
Default1	Default	DeliveryTime	2 and 4	(Amazon, 2022)
RequestToCancel	Timeout	uniform(main. MaxDeliveryTime, main.MinDeliveryTime)	3 and (4 or 5)	(ASOS, 2022)
OnTime	Default	1	3 and 4	(ASOS, 2022)
Overtime	Condition	time()>=1	3 and 5	(Farfetch, 2022)

WaitingProduct Arrived	Timeout	1		(Amazon, 2022)
Decision1	Timeout	uniform(main. MaxTryTime, main.MinTryTime)	4 and (7 or 8)	(END, 2022)
Decision2	Condition	randomTrue(ProbOfBarcketing)	4 and 7	Assumed based on product return in a COVID-19 consumer behaviour survey
Default2	Default	uniform(main. MaxTryTime, main.MinTryTime)	4 and 8	(END, 2022)
SelectTime	Timeout	uniform(main. MaxTryTime, main.MinTryTime)	7 and (9 or 10)	(END, 2022)
TryingTheProduct	Timeout	uniform(main. MaxTryTime, main.MinTryTime)	8 and (9 or 10)	(ASOS, 2022)
SelectDesiredItem	Condition	myRandomTrue (SelectProportion)	7 and 9	Assumed based on product return in a COVID-19 consumer behaviour survey
Default3	Default	uniform(main. MaxTryTime, main.MinTryTime)	7 and 10	(END, 2022)

DecsionToKeep	Condition	myRandomTrue (ProbOfKeepProduct)	8 and 9	Assumed based on product return in a COVID-19 consumer behaviour survey
Default4	Default	uniform(main. MaxTryTime, main.MinTryTime)	8 and 10	(ASOS, 2022)
BuyNewProduct	Timeout	uniform(main. MaxOrderNewProductTime, main.MinOrder NewProductTime)	9 and 1	Assumed based on product return in a COVID-19 consumer behaviour survey
PurchaseNewProduct	Timeout	uniform(main. MaxOrderNewProductTime, main.MinOrder NewProductTime)	10 and 1	Assumed based on product return in a COVID-19 consumer behaviour survey
ReturnDeliveryTIme	Timeout	uniform(main. MaxReturnDeliveryTime, main.MinReturn DeliveryTime)	10 and (11 or 12)	(Farfetch, 2022)
ReturnFail	Condition	myRandomTrue (ProbOfCantCancel)	10 and 11	(Farfetch, 2022)
SendBackToCustomer	Timeout	1	11 and 9	(Farfetch, 2022)

Default5	Default	uniform(main. MaxReturnDeliveryTime, main.MinReturnDeliveryTime)	10 and 12	(Amazon, 2022)
RefundProcess	Timeout	uniform(main. MaxRefundProcess, main.MinRefundProcess)	6 and 12	(Farfetch, 2022)
FindNewProduct	Timeout	uniform(main. MaxOrderNewProductTime, main.MinOrderNewProductTime)	12 and 1	Assumed based on product return in a COVID-19 consumer behaviour survey

Table 2: The parameters in the statechart of Agent-based model simulation

Parameter	**Value**	**Source**
ProbOfCancel	0.271	Assumed based on product return in a COVID-19 consumer behaviour survey
ProbOfKeepProduct	0.118	Assumed based on product return in a COVID-19 consumer behaviour survey

ProbOfCantCancel	0.1	Assumed based on product return in a COVID-19 consumer behaviour survey
ProbOfNotInTime	0.3	Assumed based on product return in a COVID-19 consumer behaviour survey
ProbOfBarcketing	0.251	Assumed based on product return in a COVID-19 consumer behaviour survey
SelectProportion	0.9	Assumed based on product return in a COVID-19 consumer behaviour survey

Table 3: The statistics in time stack chart of Agent-based model simulation

Name	**Conditions**
NCancellingOrder	item.inState(Consumer.CancellingOrder)
NKeepProduct	item.inState(Consumer.Keep

	Product)
NReturnProduct	item.inState(Consumer.ReturnProduct)
NRefunded	item.inState(Consumer.Refunded)
NCantReturn	item.inState(Consumer.CantReturn)
NOrderCancelled	item.inState(Consumer.OrderCancelled)
NCantStopDelivery	item.inState(Consumer.OrderCancelled)
NReceivingProduct	item.inState(Consumer.ReceivingProduct)
NWaitingOrder	item.inState(Consumer.WaitingOrder)
NBracketing	item.inState(Consumer.Bracketing)

Table 4: The data in time stack chart of Agent-based model simulation

Title	**Value**
ReturnProduct	consumers.NReturnProduct()
Refunded	consumers.NRefunded()

KeepProduct	consumers.NKeepProduct()
CancelOrder	consumers.NCancellingOrder()
ReceivingProduct	consumers.NReceivingProduct()
Bracketing	consumers.NBracketing()
WaitingOrder	consumers.NWaitingOrder()

By setting up the state in the statechart and setting the values in each transition, we came up with a model to describe the customer's decisions about a product return that the processes in the model can compare. Compare that to the flowchart diagram in chapter 3.2. The following section is the validation of the agent-based model simulation.

3.3.2 Validation of Agent-based model simulation (ABMS)

In Chapter 3.3, Onggo and Foramitti (2021) point out that a model must represent the real world being modelled. The Agent-based model simulation must capture the key agent, the key behaviours, and the essential elements of the system. Hence, there is a notion of validity in whether or not this model is representative enough to use in a computer experiment. A modeller may fail to capture key elements of the system, simplifying them incorrectly. So, verification and validation are essential. Due to the simulation model comparing the "real world" with the virtual world that represents the real world, the simulation model's output is representative of the pattern observed in the real-world system being modelled. So, validation assesses the representativeness of a model—validation concerns with building the suitable model and verification concerns with building the model right. In the agent-based simulation, we model individual behaviours. We want to observe the interaction between individuals and how it generates a pattern that can be observed at the population level. An ABS model has two levels of behaviours: individual and population. To ensure that the behaviour of the individuals that are generated reflects the behaviours of individuals in the real world, likewise, the pattern that is generated demonstrates the pattern in the real world. There are two levels of validation in the ABS model: micro-validation and macro-validation. The question that we typically ask during a micro-validation is whether or not we have included all key agents, whether or not we have included all key behaviours, Is the proportion of agent types representative? Is the environment representative? And Is the network structure representative? At the macro level, The question we typically ask is, Does the simulation output represent the pattern observed in the real world? And Can the simulation output at the population level be explained from the behaviour of agents in the model? Collecting data about the mechanism that drives human behaviour is challenging. Big data can help with ABS model validation using empirical data. However, in ABS, we model the mechanisms that drive observable behaviours. Big data does not collect these, and big data does not capture the internal mechanism. Therefore, we need to use other techniques to define the approach, which is subjective or objective, observable system or non-observable system. This project is the subjective method. Therefore, we will run our model in front of the decision maker or expert and then get feedback from them on whether the system's behaviour is reasonable and representative of the real world. The second one is exploring model behaviour. We run our model with the different number inputs and try to understand and observe whether the behaviour is reasonable. For example, if we increase the refund process time, we should expect the average number of customers who decide to buy the new product to decrease. By changing the inputs to the model and then assessing the impact on the model output, we can better understand whether or not the model works as expected.

CHAPTER 4. RESULTS ANALYSIS

Chapter 4 begins with the verification and validation of the simulation model result, followed by output data analysis, which includes the time stack chart in 90 days simulation. Furthermore, in the output data analysis section, comparing the number of customers in each state at a different time of the simulation model, describing the decision-making and behaviours of the customer.

4.1 Validation of the agent-based model simulation result

From Chapter 3.3.2, this model is a subjective model. Thus, exploring model behaviour, running our model with the different number inputs and trying to understand and observe whether the behaviour is reasonable (Onggo and Foramitti, 2021). After we run a model with specific value for validating the model in 90 days as shown in Figure 20. The time stack chart indicates that according to the time stack chart, some customers decide to cancel after an order has been placed. After the customer receives the item, most customers have the desire to return the item in this state, along with the customers who decide to cancel their orders but not before the products are prepared. The customers who cancelled and received the product began to receive a refund. Then, the customers are divided into two large groups: those who decide to keep the product and those who decide to return the product. And the person who returns the product receives the refund afterwards. Everything is a cyclical operation as the customer has the opportunity to repurchase the product after the return, after the refund, or even the person who keeps the item.

From the reasonableness of the model, when everything is set to the maximum value, a large cycle occurs with each interval significantly different because the interval time is increased at the maximum value, as shown in Figure 21. And when all the minimum values are adjusted, the result will be a continuous picture of the distribution of customers in various states. Because the entire process time is fast paced, as shown in Figure 22. Therefore, the model simplifies and assesses the model as comparable to the real world. But there are still some limitations in modelling that will be discussed later in Chapter 5.

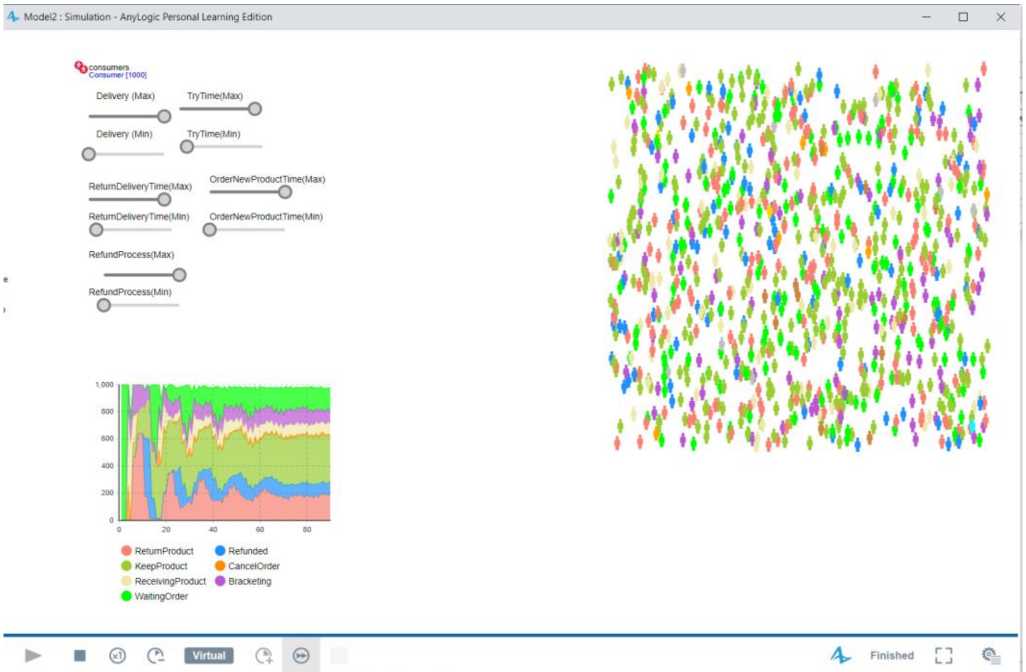

Figure 20: The result when setting in specific value for validation agent-based model simulation

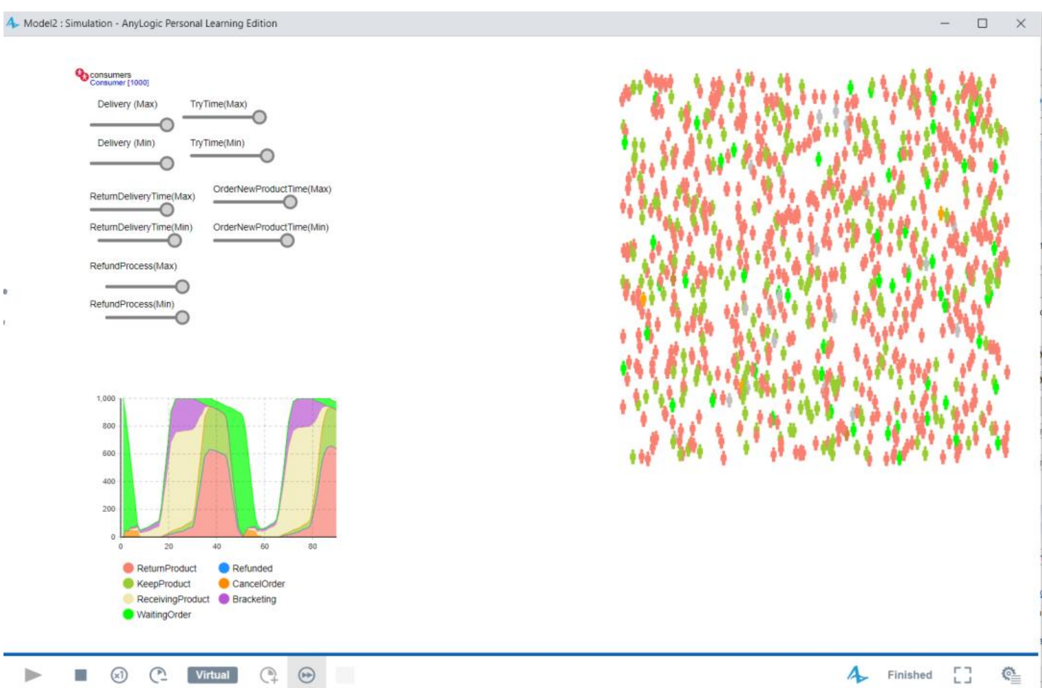

Figure 21: The result when setting in extreme value for validation agent-based model simulation

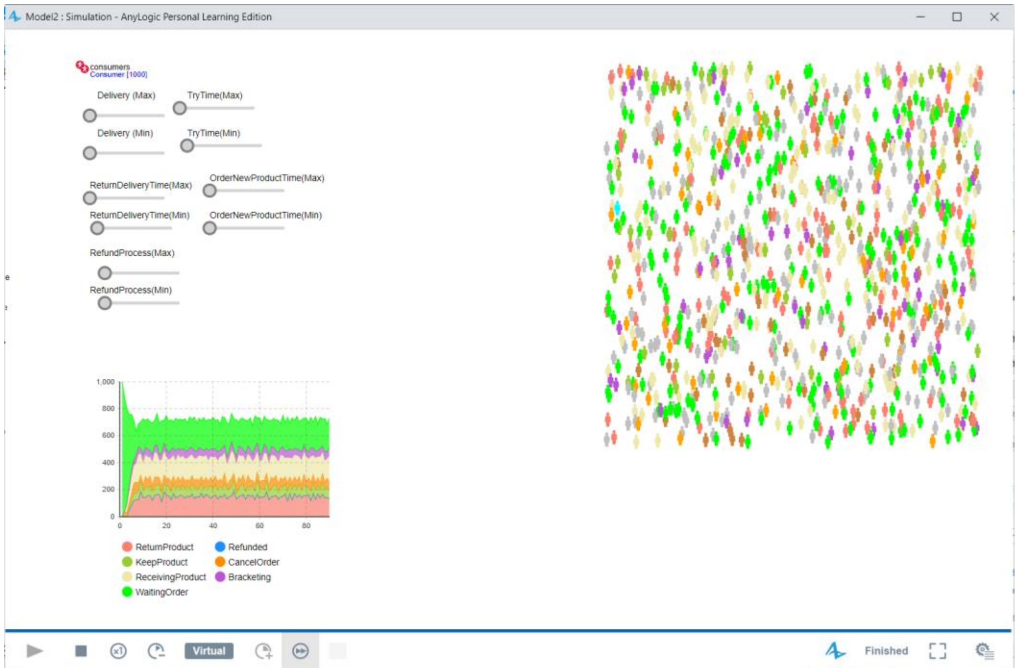

Figure 22: The result when setting in lowest value for validation agent-based model simulation

4.2 Output data analysis

The purpose of the project/questions of the research is to describe the decision-making or behaviour of consumers in return. Thus, the results are presented as a time stack chart indicating the number of customers in each state that should be considered when making consumer decisions. The time stack chart contains the state of "ReturnProduct", "Refunded", "KeepProduct", "CancelOrder", "ReceivingProduct", "Bracketing", and "WaitingOrder" as shown in figure 23.

Since the time setting and values are used in the uniform function. And conditional values are probabilistic. Consequently, the outcomes are quite consistent and can be rationalised. Initially, 1,000 customers decide to place an order and are placed in the pending order waiting time ("WaitingOrder"). During the gradual delivery of orders, some customers decide to cancel the product and obtain the "CancelOrder" state. Customers who submit a cancellation request are divided into two groups: those who can cancel the product in time, which leads directly to the refund procedure, and those who cannot cancel the product in time. And another group of customers who cannot return the product on time must receive it according to the original schedule. Customers who initially cancel their order might have the probability of changing their decision to keep the products. The customer who intends to place a bracketing order ("Bracketing") Goes to product selection to consider returning most of the items. As the remaining customers receive the product, the state "Receiving Product" will be updated to reflect the product's condition. After that, the customer's return requests from all states will be consolidated into one state. "ReturnProduct". When the customer who cancels the product begins receiving a refund, the product's state changes to "Refunded."

The results of this model run for 90 days or 90 model time. It illustrates the cycles in each state, which all result in a consumer shift over time. The first wave of pick-up and return cycles had higher peaks than subsequent cycles due to the fact that this model began with all customers purchasing simultaneously. And the reason why the next cycle's peak is lower than the previous cycle's is that the delay in consumers making new purchases causes customers to distribute more in each state.

The purpose of this investigation is to describe consumer decision-making. It illustrates the uniform distribution across each state. Customers make decisions gradually. Even if the customer initially decides to cancel the product, if they are unable to do so in time, the product will be delivered to their address, requiring them to make a second decision after receiving the product. The customer in this bracketing state has also decided that they must return nearly sure of the product because they ordered the same product in multiple sizes or colours. However, even though the bracketing state is a definite return decision, there is also a high probability that they will keep the item, so it differs from the received product state, where the customer must consider and make the most challenging decision. Depending on several factors, including the product's condition, the store's return policy, the customer's expectations, etc., the decision to return a product can take more or less time. Consider purchasing a new product after returning an old one, receiving a refund, or desiring additional items. According to the results of this study, there are various decision points. Eventually, the decision is a result of the original decision point. There is a continuation of the decision's cause and effect. There is a distinction between pre-decision making and future decisions, which necessitates further research. Figures and information on all results are shown in the appendices.

This is primarily an initial model for explaining consumer decisions regarding product returns. In Chapter 5, we will discuss additional limitations and techniques that can be applied in the future to develop this research further.

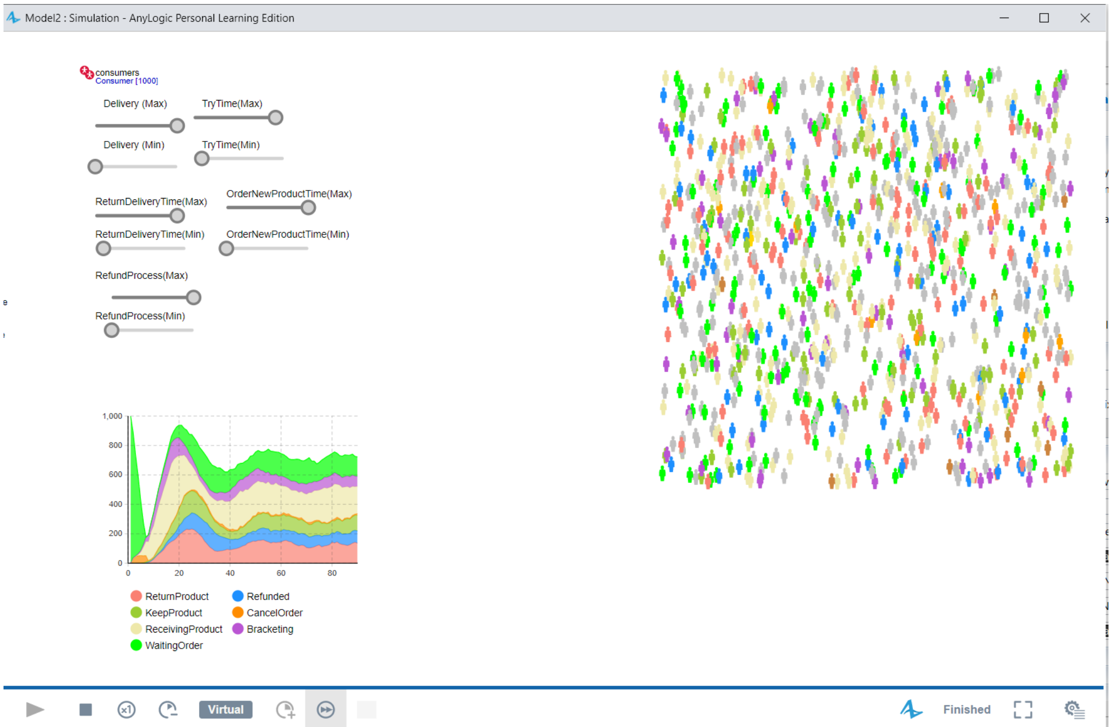

Figure 23: The result agent-based model simulation in 90 days

CHAPTER 5. DISCUSSION AND LIMITATION

This chapter will begin with a discussion of the ABMS model's findings and a literature review. discuss the limitations of Agent-based model simulation development. Retailers and practitioners would benefit from considering the model's limitations when evaluating simulation results.

From literature review, as stated in Chapter 2.1.1 Original research has designed supply chain processes to be as efficient as possible in terms of operator costs and system integration (Frei, et al., 2022). This research is essential for the development of the consumer decision-making flow diagram. The change from consumer and retail action to consumer states influences return process decisions. In addition, research in Chapter 2.1.2 suggests that retailers overlook the hidden costs of product return services, resulting in overall business cost issues. So, this research adds dimension to decision analysis in multiple aspects, such as the customer's intent to return a product from an over-order or bracketing. This model's key decision-making points are enhanced by adding consumer decision-making beyond the general product return process. As part of the literature review for Chapter 2.2, the discussion of consumer decision-making is analysed in detail. This is because the important decision to return products is reflected in the purchase decision. Therefore, the establishment of a return policy is a crucial retailer action that has a direct impact on customer decisions. This allows this research to be considered alongside other factors contributing to making models more representative of actual processes. Many research have been presented for modelling the decision-making of consumers or people (Roozmand, et al., 2011), (McHugh, et al. 2016), (Namany, et al., 2020), and (Bozdoğan, et al., 2022). The outcomes of these models are represented as graphs depicting the number of individuals making decisions in various ways, developing strategies based on results, implementing statistical values to determine the correct outcomes, etc.

The main objective of this research is to describe the consumer's decision or behaviour in returning merchandise. This is determined by the results shown in the time stack chart. As a result, we can see the distribution of customers in various states related to returns. Moreover, different decision-making patterns occur in this process. Many processes are continuous, and some can occur spontaneously. However, this model was set up to create a simplified model based on publicly available data and data from Product Returns in a COVID-19 World-Jan 2022 Survey. Therefore, the values of variables and transitions need to be analysed from a variety of sources. Moreover, the functions used in the model are mostly constants, uniform functions, and probabilities. This can add more sophisticated techniques for defining individual variables and multiple transitions to make the model more realistic. For example, Adding various conditions to the status of a cancellation request because there are many reasons for this, and each customer's decision is different. As with the return status, there are many reasons, and there are overlapping decisions, such as intentional return before receiving the product. Or the return of products due to various reasons discussed in Chapter 2. Further, increasing the agent or consumer terms is important to make the agent more complex and able to classify groups. For example, trade is more like adding agent conditions about age group, financial status, income or education level, etc. The different conditions of the agents will result in other decisions. In making this model, there are limitations regarding time, data acquisition, and model development. However, this research can build on the complexity of the model to cover all possibilities compared to the actual situation. This includes examining subjective models that require an expert or researcher to evaluate the model's validity or logic. Various configuration methods only examined this model.

Developing a strategy based on an explanation of consumer decisions regarding returns entails creating a model for dealing with each customer status, e.g., by examining the distribution of customers across each state. Retailers should establish policies that reduce the number of returns while maintaining customer satisfaction, or consider a workforce to support customers in different states during the return process, etc.

CHAPTER 6. CONCLUSION AND RECOMMENDATION IN FUTURE RESEARCH

This chapter provides a summary of the model-building procedure and simulation results. Additionally, implicatons future research is considered to improve the accuracy of the model.

6.1 Conclusions

This dissertation aims to develop an agent-based model to describe customer decision-making about product returns. This study began with a search for information and a literature review of three fields. Returning products in omnichannel retail, Customer purchasing and return decision-making and agent-based simulation model. The implementation starts with analysing the COVID-19 consumer behaviour product return survey and summarising knowledge for modelling. Based on a review of the literature concerning the return procedure and customer decision-making. This has led to the development of a process that considers the customer's return decision-making. Lastly, the development of a simulation based on an agent-based model to describe consumer decisions and behaviours regarding product returns. The Model's outcomes illustrate the various possible states of the consumer, from the purchase decision to the return of the product. Other forms of research were unable to explain the consistency of decision-making and the decision-making which is not underlying a typical return process. as well as describe customer behaviour at a given time based on the model's variable settings.

The results of describing customer decisions at various points in the process reveal several fascinating choices: A customer's decision that has changed due to the previous decision's conditions, such as a customer who intends to cancel an order but cannot do so in time. They must be waiting for the order. However, after receiving the product, the customer who had initially cancelled the order decided to keep it because they were satisfied with it. Some customers intentionally order products to keep only a small number of items and return the remainder to the store. In this case, there are two additional possibilities: the customer will return the product. Either return all items ordered or return the vast bulk of products selected as satisfied. However, they will not be able to keep all of the products, as the initial order clearly indicates the need for a bracketed order.

6.2 Implications

By evaluating the ABMS model, retailers or merchants can determine the ideal return policy by analysing consumer behaviour that influences decisions beyond those previously studied. More than that, merchandising operators can plan their workforce to deal with decision-making in various states of consumers. In terms of practitioners conducting research involving modelling to describe consumer decision-making or behaviour with ABMS methods, practitioners take advantage of this research's approaches and modelling methods. However, there are several points for improvement in the recommendation and further research section.

6.3 Recommendation for future research

There are limitations of this research in chapter 5. Consequently, this chapter discusses methods for improving or expanding future research.

Due to the limitation that we cannot find all variables, or some data is still unclear, the creation of essential functions in the model operation is not as complicated as expected. Therefore, the research should collect more information, whether it's research studies, statistical data collection, interviews with experts or stakeholders, discussions in focus groups, experiments, or analytical approaches.

Considering all aspects of the data used in the modelling increases the coverage of the datasets that will be utilised. Different consumer conditions, such as gender, education level, socioeconomic standing, etc., are also significant and have a significant impact on decision-making. These details should be considered in conjunction with the current return procedure to ensure that a more complete model is created. Model validation is also essential because it necessitates the consideration of operations during model execution by experts or process stakeholders in order to provide feedback that makes the model more realistic.

6.4 Personal reflection

There are some challenges from the dissertation topic to the end. This is because it is a topic related to describing consumers' decision-making about returning the product is complex, and there is not much research to match this purpose. Much of the research focuses on consumer decision-making regarding the purchase, so building simulation models about consumer decisions about returns are challenging. Moreover, designing and modelling require a deeper understanding of proficiency in modelling and variable assignments with quality and accurate data and clearer model validation. The importance of self-improvement in both hard and soft skills precisely

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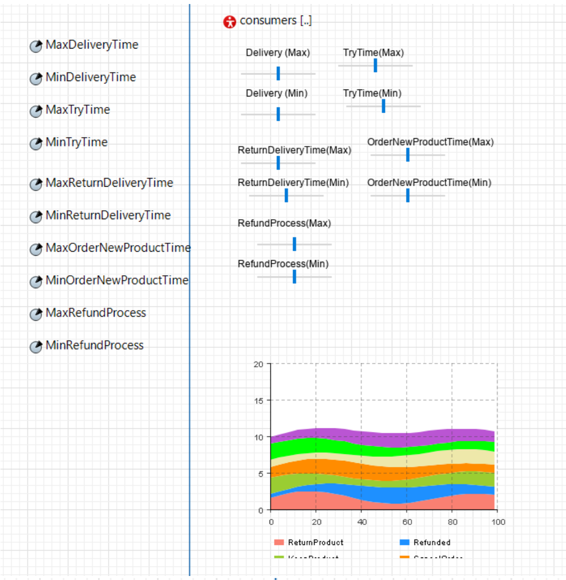
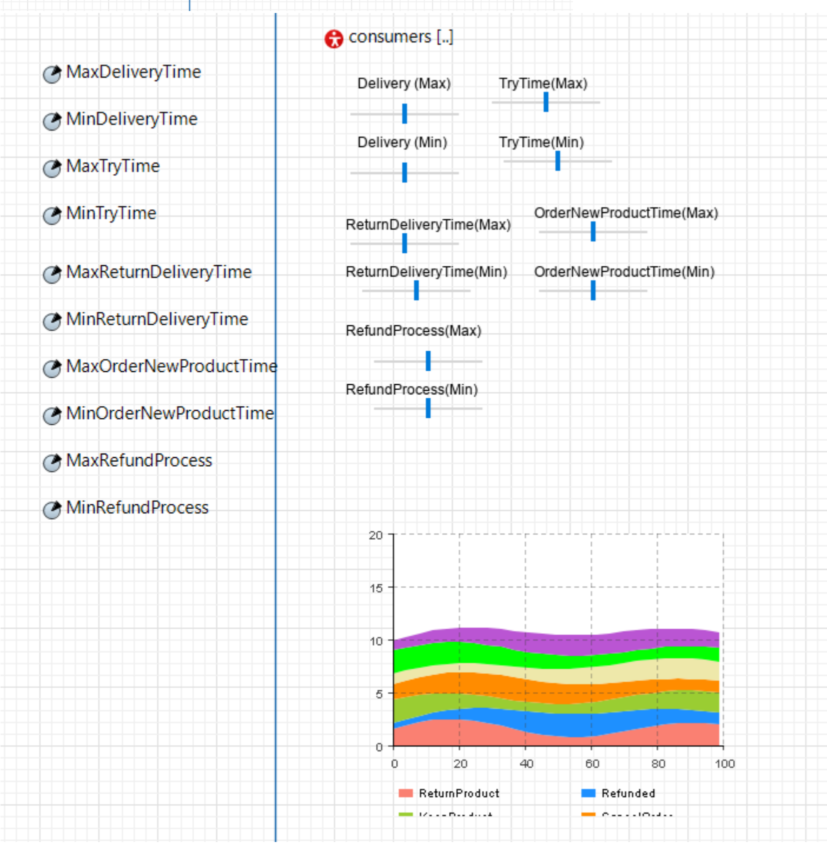
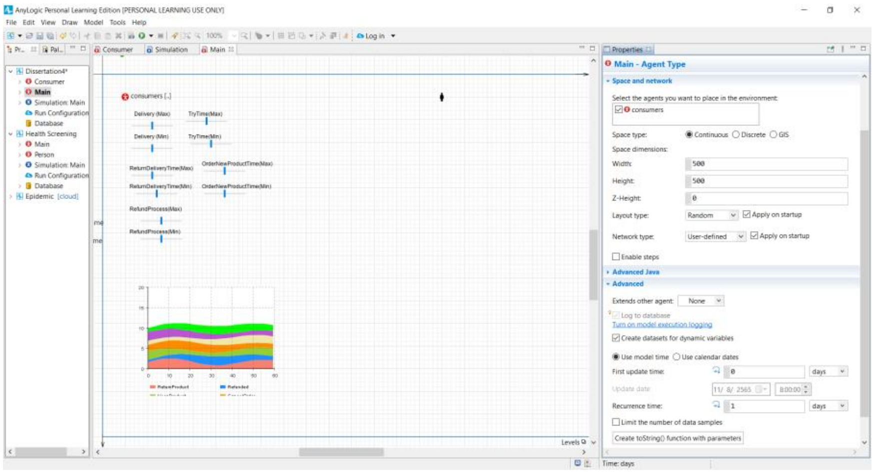
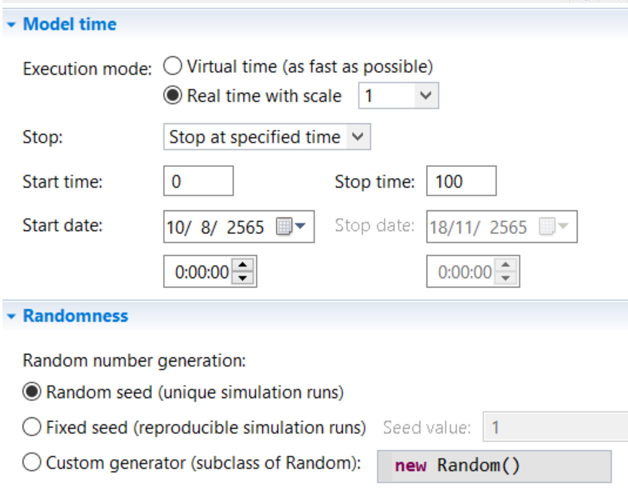
APPENDICES

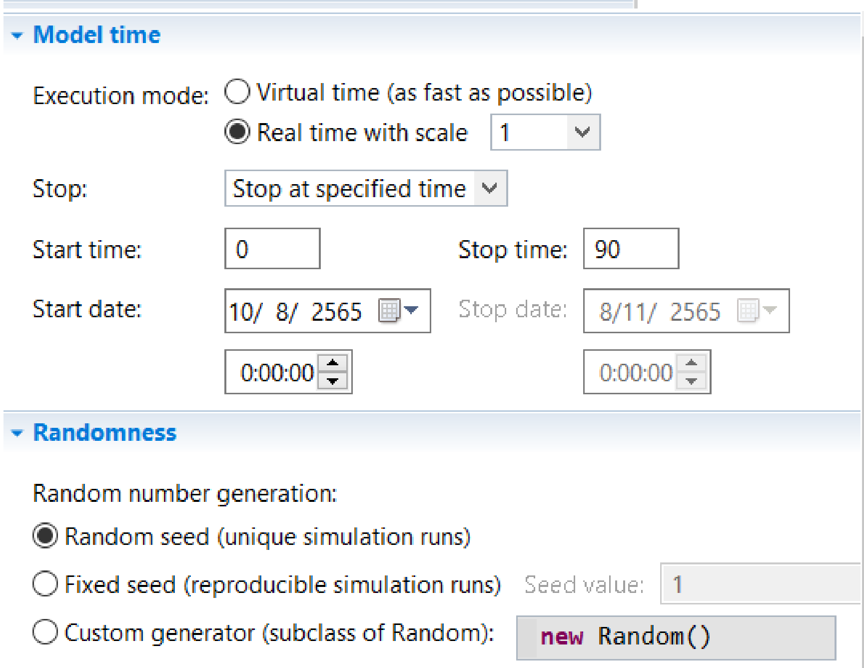
Appendix I: The Agent-based model simulation

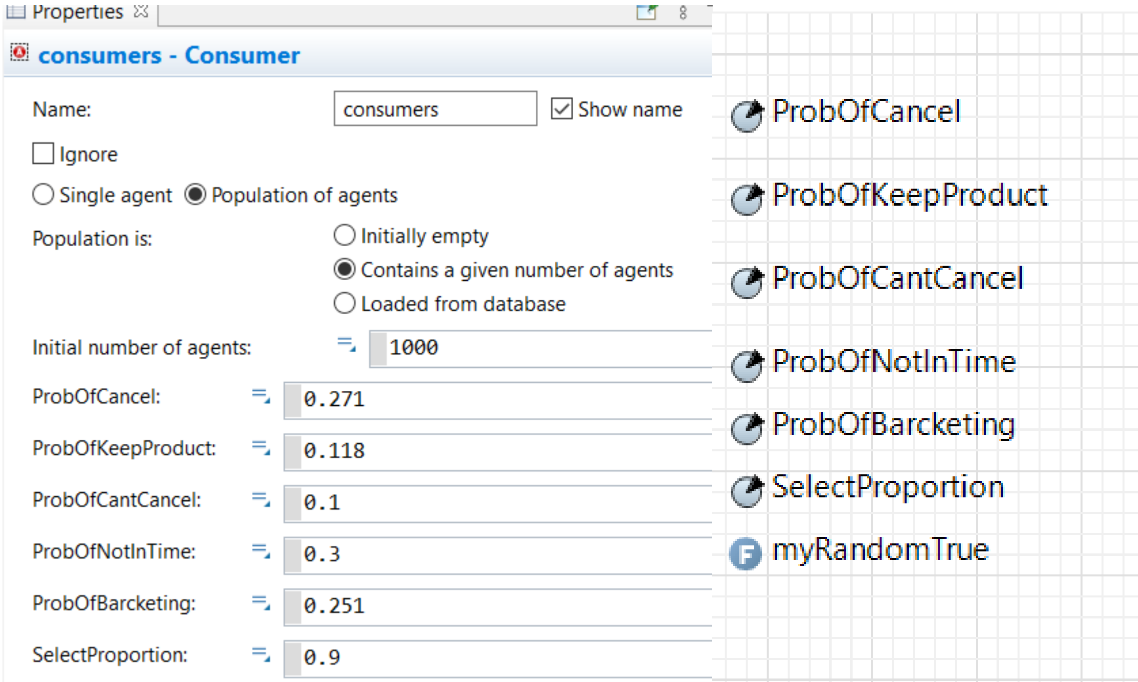


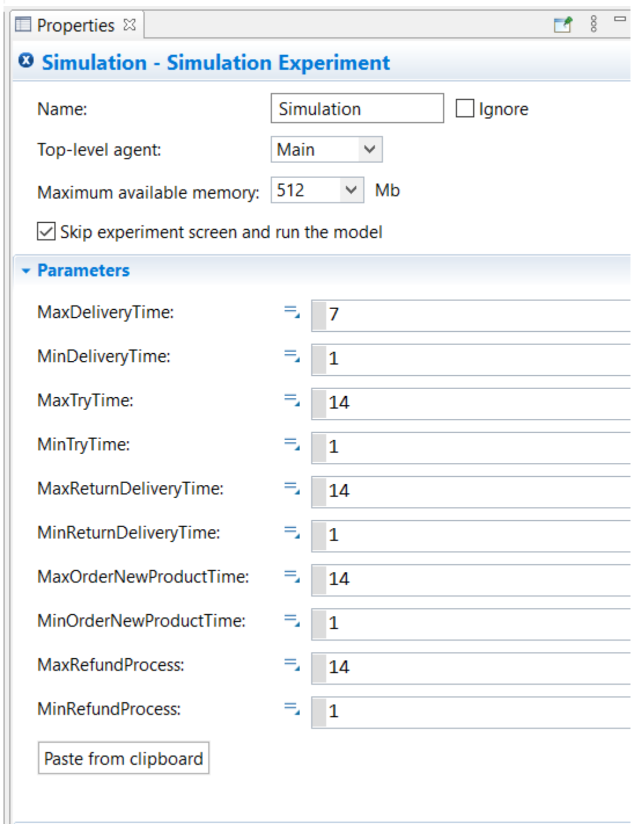


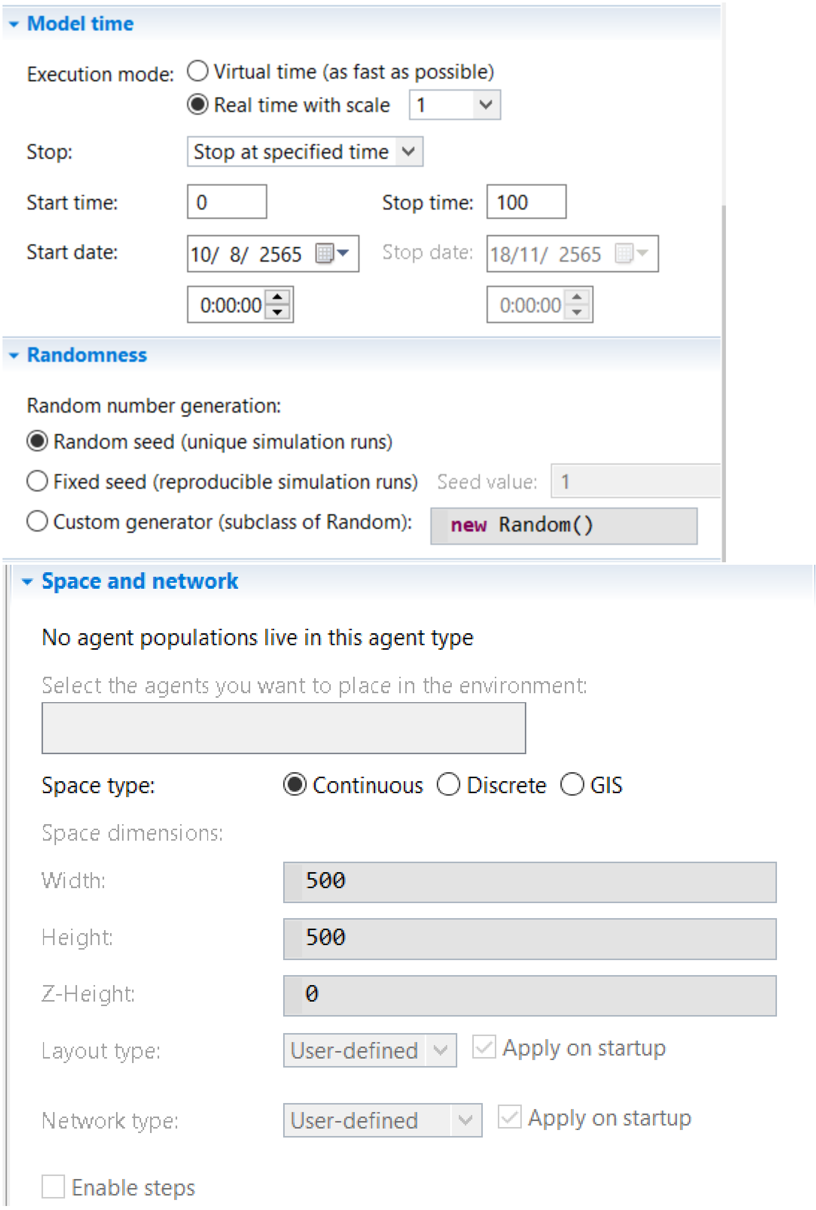

Main - Agent Type
Space and network
Advanced Java
Advanced

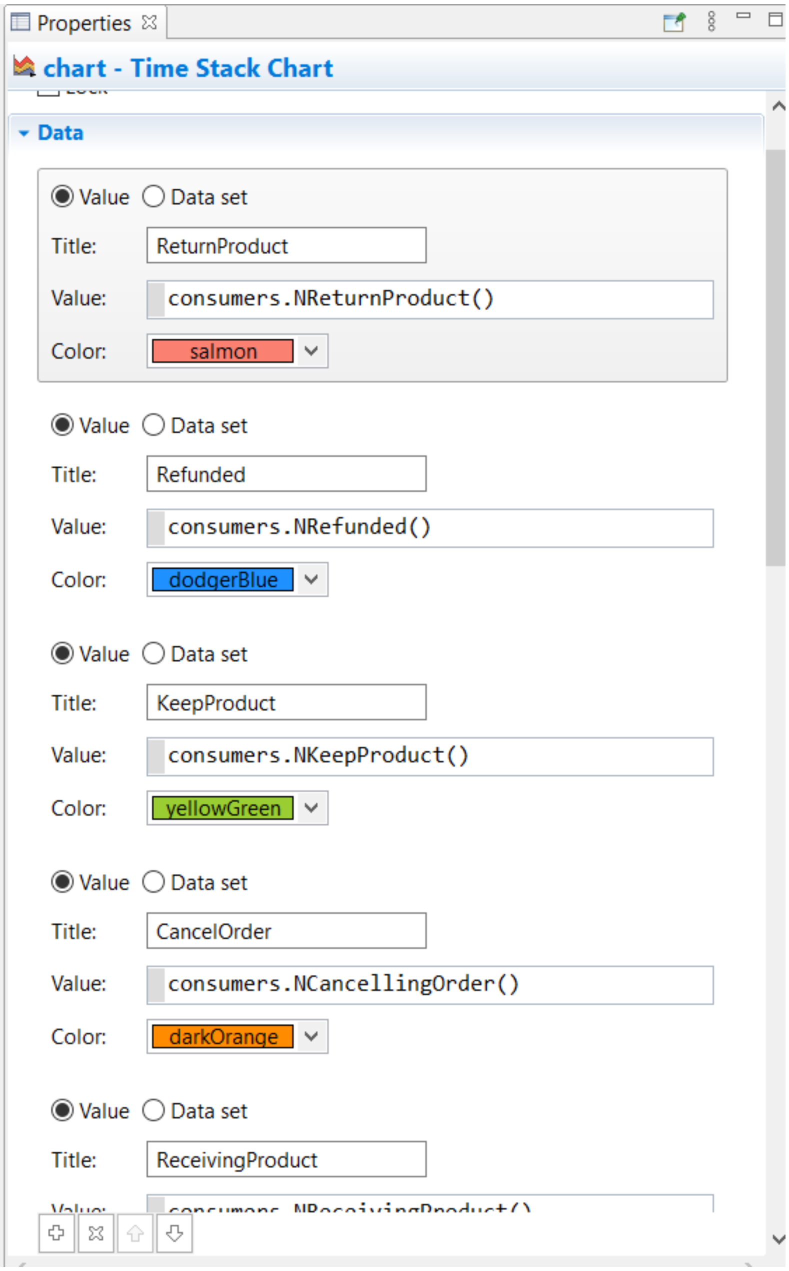

Model time
Execution mode:
Virtual time (as fast as possible)
Real time with scale
1
Stop:
Stop at specified time
Start time:
0
Stop time:
100
Start date:
10/ 8/ 2565
Stop date:
18/11/ 2565
0:00:00
0:00:00
Randomness
Random number generation:
Random seed (unique simulation runs)
Fixed seed (reproducible simulation runs)
Seed value:
1
Custom generator (subclass of Random):
new Random()

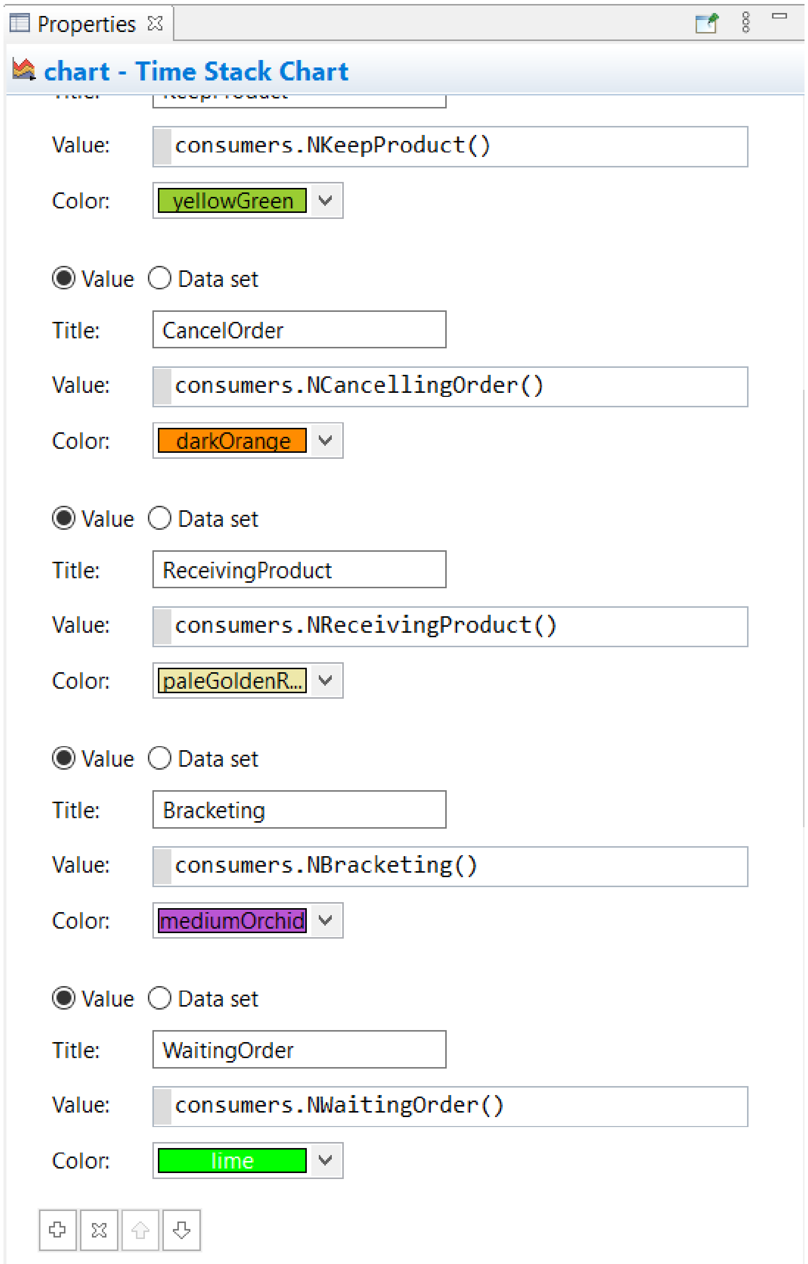

Model time
Execution mode:
Virtual time (as fast as possible)
Real time with scale
1
Stop:
Stop at specified time
Start time:
0
Stop time:
90
Start date:
10/ 8/ 2565
Stop date:
8/11/ 2565
0:00:00
0:00:00
Randomness
Random number generation:
Random seed (unique simulation runs)
Fixed seed (reproducible simulation runs)
Seed value:
1
Custom generator (subclass of Random):
new Random()

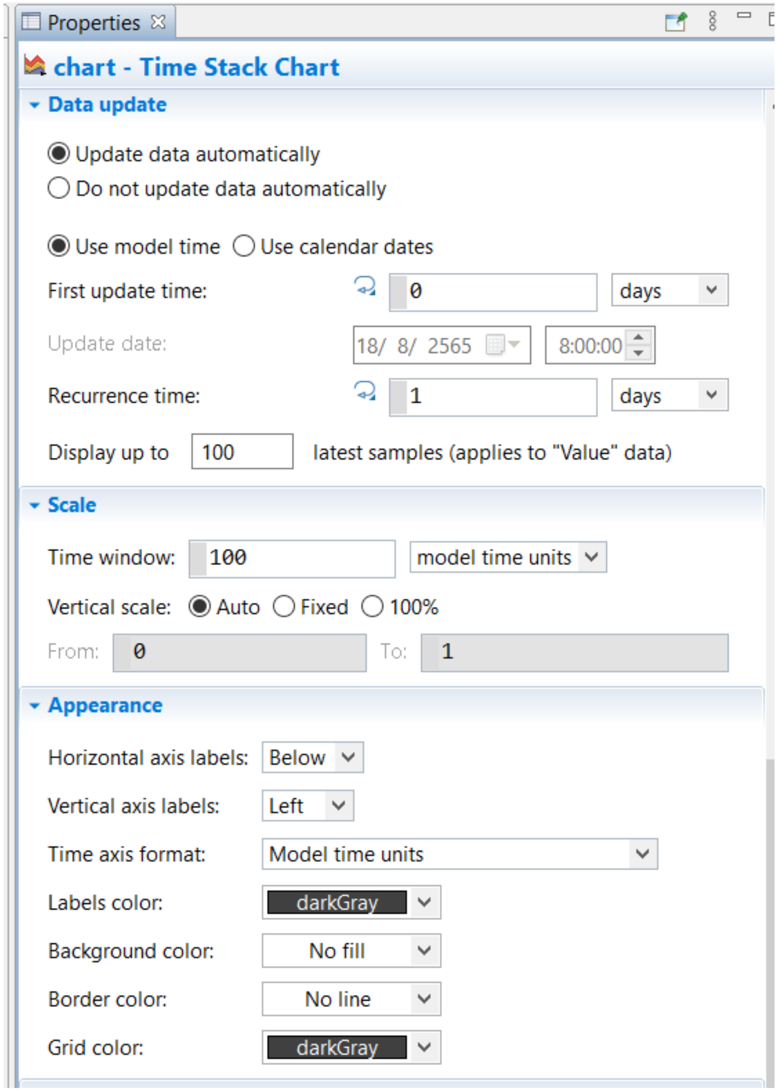

Properties
consumers - Consumer
Name:
consumers
Show name
Ignore
Single agent
Population of agents
Population is:
Initially empty
Contains a given number of agents
Loaded from database
Initial number of agents:
1000
ProbOfCancel:
0.271
ProbOfKeepProduct:
0.118
ProbOfCantCancel:
0.1
ProbOfNotInTime:
0.3
ProbOfBarcketing:
0.251
SelectProportion:
0.9
ProbOfCancel
ProbOfKeepProduct
ProbOfCantCancel
ProbOfNotInTime
ProbOfBarcketing
SelectProportion
myRandomTrue

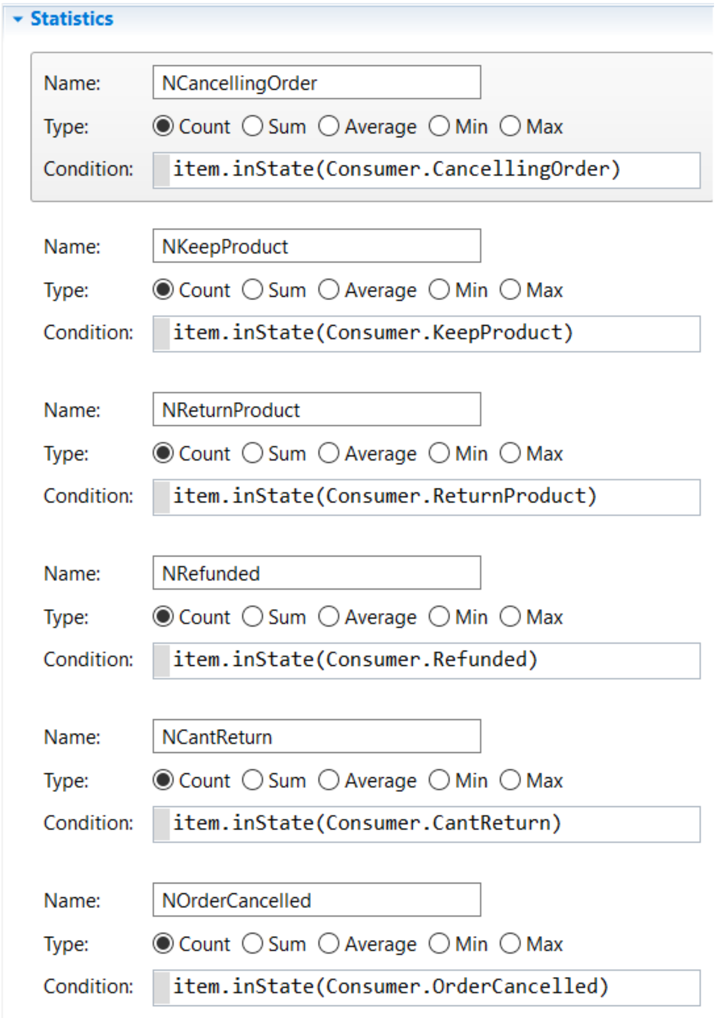

Properties
Simulation - Simulation Experiment
Name:
Simulation
Ignore
Top-level agent:
Main
Maximum available memory:
512
Mb
Skip experiment screen and run the model
Parameters
MaxDeliveryTime:
7
MinDeliveryTime:
1
MaxTryTime:
14
MinTryTime:
1
MaxReturnDeliveryTime:
14
MinReturnDeliveryTime:
1
MaxOrderNewProductTime:
14
MinOrderNewProductTime:
1
MaxRefundProcess:
14
MinRefundProcess:
1
Paste from clipboard

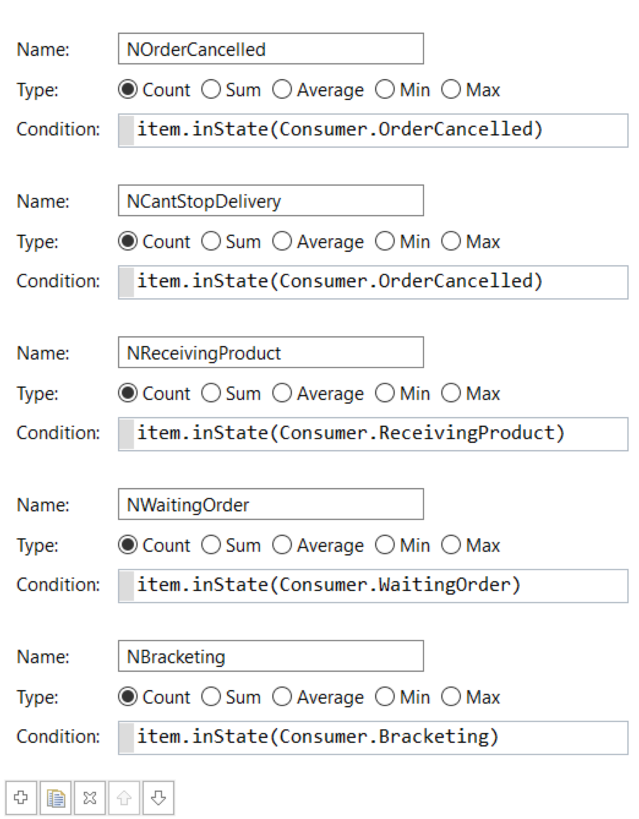

Model time
Execution mode:
Virtual time (as fast as possible)
Real time with scale
1
Stop:
Stop at specified time
Start time:
0
Stop time:
100
Start date:
10/ 8/ 2565
Stop date:
18/11/ 2565
0:00:00
0:00:00
Randomness
Random number generation:
Random seed (unique simulation runs)
Fixed seed (reproducible simulation runs)
Seed value:
1
Custom generator (subclass of Random):
new Random()
Space and network
No agent populations live in this agent type
Select the agents you want to place in the environment:
Space type:
Continuous
Discrete
GIS
Space dimensions:
Width:
500
Height:
500
Z-Height:
0
Layout type:
User-defined
Apply on startup
Network type:
User-defined
Apply on startup
Enable steps


Properties
chart - Time Stack Chart
Data
Value
Data set
Title: ReturnProduct
Value: consumers.NReturnProduct()
Color: salmon
Value
Data set
Title: Refunded
Value: consumers.NRefunded()
Color: dodgerBlue
Value
Data set
Title: KeepProduct
Value: consumers.NKeepProduct()
Color: yellowGreen
Value
Data set
Title: CancelOrder
Value: consumers.NCancellingOrder()
Color: darkOrange
Value
Data set
Title: ReceivingProduct


Properties
chart - Time Stack Chart
Value: consumers.NKeepProduct()
Color: yellowGreen
Value Data set
Title: CancelOrder
Value: consumers.NCancellingOrder()
Color: darkOrange
Value Data set
Title: ReceivingProduct
Value: consumers.NReceivingProduct()
Color: paleGoldenR...
Value Data set
Title: Bracketing
Value: consumers.NBracketing()
Color: mediumOrchid
Value Data set
Title: WaitingOrder
Value: consumers.NWaitingOrder()
Color: lime


Properties
chart - Time Stack Chart
Data update
Update data automatically
Do not update data automatically
Use model time
Use calendar dates
First update time:
0
days
Update date:
18/ 8/ 2565
8:00:00
Recurrence time:
1
days
Display up to
100
latest samples (applies to "Value" data)
Scale
Time window:
100
model time units
Vertical scale:
Auto
Fixed
100%
From:
0
To:
1
Appearance
Horizontal axis labels:
Below
Vertical axis labels:
Left
Time axis format:
Model time units
Labels color:
darkGray
Background color:
No fill
Border color:
No line
Grid color:
darkGray


Statistics
Name: NCancellingOrder
Type: Count Sum Average Min Max
Condition: item.inState(Consumer.CancellingOrder)
Name: NKeepProduct
Type: Count Sum Average Min Max
Condition: item.inState(Consumer.KeepProduct)
Name: NReturnProduct
Type: Count Sum Average Min Max
Condition: item.inState(Consumer.ReturnProduct)
Name: NRefunded
Type: Count Sum Average Min Max
Condition: item.inState(Consumer.Refunded)
Name: NCantReturn
Type: Count Sum Average Min Max
Condition: item.inState(Consumer.CantReturn)
Name: NOrderCancelled
Type: Count Sum Average Min Max
Condition: item.inState(Consumer.OrderCancelled)



Appendix II: The results of Agent-based model simulation

	ReturnProduct	Refunded	KeepProduct	CancelOrder	ReceivingProduct	Bracketing	WaitingOrder
1	0	0	0	0	0	0	1000
2	0	0	0	36	0	0	851
3	0	0	0	46	1	3	677
4	0	0	0	51	9	5	521
5	0	0	2	50	25	9	334
6	0	0	3	48	58	17	154
7	2	0	7	43	95	28	2

8	9	0	9	0	129	45	1
9	16	0	11	0	185	59	3
10	30	0	12	0	212	83	5
11	48	1	24	0	252	96	4
12	63	4	36	1	290	112	2
13	76	9	41	0	321	119	11
14	93	14	53	1	345	128	18
15	117	20	57	0	365	138	23
16	135	24	68	0	391	139	35
17	147	31	88	3	408	141	43
18	156	41	96	5	408	133	59
19	171	49	106	4	392	129	74
20	194	60	119	6	353	121	85
21	205	67	135	5	319	100	106
22	220	81	153	6	275	75	106
23	231	84	155	8	238	68	120
24	228	98	159	5	196	60	130
25	233	109	150	7	167	53	155
26	226	112	150	11	140	42	169
27	211	117	148	13	117	39	178
28	195	118	139	10	103	32	191
29	179	120	132	19	92	37	188
30	150	132	128	12	96	36	189

31	131	141	111	11	96	40	188
32	110	136	95	16	105	38	188
33	98	132	85	8	123	42	178
34	84	124	76	13	135	47	179
35	81	113	78	10	140	54	171
36	83	101	71	13	159	56	165
37	85	94	67	20	164	52	153
38	89	84	62	12	172	58	143
39	95	72	54	15	183	64	137
40	90	72	55	10	194	71	144
41	95	66	54	17	205	78	122
42	98	66	55	7	224	76	117
43	102	61	58	7	242	82	119
44	109	61	70	13	240	75	110
45	118	62	64	4	237	84	111
46	123	63	71	9	235	86	105
47	138	67	72	6	216	92	111
48	142	64	84	6	220	96	115
49	150	68	93	10	213	89	109
50	149	66	104	4	224	91	117
51	155	74	104	14	212	86	121
52	155	81	98	8	210	79	126
53	159	81	103	4	204	76	128

54	151	84	103	5	198	72	149
55	145	89	102	12	206	66	155
56	138	76	103	10	208	66	160
57	143	79	96	7	209	65	160
58	140	84	99	11	212	61	148
59	143	77	100	7	205	59	163
60	144	75	101	11	196	65	153
61	153	76	102	13	180	64	150
62	155	69	96	14	187	59	146
63	148	75	99	14	176	58	140
64	145	72	98	8	173	62	146
65	133	84	93	7	178	63	146
66	124	85	96	7	182	59	154
67	118	80	95	13	175	59	166
68	123	80	94	12	178	58	152
69	120	80	86	7	182	66	155
70	106	85	84	4	190	68	168
71	104	74	84	15	202	68	170
72	106	75	83	15	201	67	147
73	111	76	90	11	205	63	138
74	119	71	93	10	201	60	121
75	124	67	92	8	206	64	124
76	111	72	88	6	227	64	133

77	118	72	82	8	233	72	128
78	120	69	80	3	237	75	141
79	126	65	82	8	234	76	143
80	143	64	80	6	229	80	144
81	138	66	83	14	238	76	141
82	145	71	84	13	223	70	141
83	133	77	87	7	227	65	135
84	128	70	88	3	226	67	145
85	125	75	97	9	212	71	147
86	120	80	103	6	212	73	140
87	126	76	98	6	207	75	146
88	136	83	97	9	197	77	142
89	142	82	102	8	186	72	134
90	136	83	107	11	185	68	132