Strategic Returns Prevention in E-Commerce: Simulating Financial and Environmental Outcomes Through Agent-Based Modeling

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Abstract: Product returns pose an environmental and financial burden on manufacturers and online retailers worldwide, especially in the fashion sector. Over 50% of all ordered garments end up being returned, which gives rise to an ongoing search for approaches to successfully manage returns or to avoid returns in the first place. For both approaches, an accurate prediction of returns can be useful, since it allows for an improved inventory risk assessment and strategic reselling of garments, while also providing crucial information on common drivers of return rates. This study focuses on preventive strategies in the context of customers placing selection orders in online shops. An Agent based approach provides insight into the outcomes of three different return prevention strategies, which are compared with the original outcome of real world data from a German clothing manufacturer selling garments for special occasions. The four outcomes are analysed in terms of their financial and environmental impact, utilising common life cycle assessment strategies.

1 INTRODUCTION

The global fashion e-commerce market has continuously grown each year over the past years alongside the growth of online retail in general. With fashion e-commerce being forecast to reach over US 781.5 billion in 2024 and an estimate to reach US 1.6 trillion by 2030, the fashion sector is the largest B2C e-commerce market segment to date (Statista, 2024). Alongside the increasing revenue comes the financial and environmental burden of an increasing volume of product returns. In 2022, most product returns were associated with the fashion sector, for example in Germany, a share of 91% of returns were fashion items (Forschungsgruppe Retourenmanagement, 2022). Due to the additional costs that returns impose on online retailers due to the necessary reprocessing steps before reselling the items, many businesses opt to send returned items to landfills. In 2021 in Germany, approximately 17 million returned items were disposed, while other European countries exhibit even higher disposal rates (Forschungsgruppe Retourenmanagement, 2022). Another issue with returns is posed by the large amount of parcel shippings, where each returned package generates an average of 1.5 kg of CO_2 equivalents (Forschungsgruppe Retourenmanagement, 2022), contributing to the fashion sector being among the top three of most polluting industries. Minimising returns overall has the largest impact in reducing environmental harm and financial strain. Strategies can be twofold - either pursuing preventive strategies with the main goal of avoiding returns in the first place, or reactive strategies aiming at improving the handling of returns in terms of sustainability, time and cost (Deges, 2021). In either case, it is important to understand the drivers of returns. The reasons for consumers to return items are diverse and may include, but not be limited to the following reasons: Unmet expectations with regards to look or quality, personal preferences, dissatisfaction with the fit, the wrong size, too much time passed between order and delivery, receiving the incorrect item, ordering for someone else. Therefore, it can be advantageous for retailerst to know when which items will likely be returned. The return reason can also be an

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important indicator of the item's condition upon return. A large quantity of fashion returns are related to size or selection of items. The latter case is given when customers order multiple versions of the same item or multiple items from the same category (like multiple dresses) with the intention of buying only one or a few of them. This very common behavior in the fashion sector is referred to as bracketing (Bimschleger et al., 2019).

This study focuses on an Agent based simulation of preventive strategies based on the targeting of selection orders by utilising awareness-raising methods in order to have customers make alterations to their shopping card in favor of the environment. This research is part of a larger scope of research that aims at developing an AI-based recommendation system for the prediction of returns and improved return management. This part of the research aims at presenting a blueprint for estimating the possible financial and environmental impact that can be achieved using the return predictions and their associated return reasons to target specific return driving behavior before an order has been placed. The first section references related work in the context of this study. The subsequent section describes the methods used for the setup of the Agent based approach and the methods used to infer the environmental impact from the outputs. Third, we analyse the outcomes of the simulation in general as well as from an environmental perspective based on material consumption.

2 RELATED WORK

This section presents a selection of work related to the topics of this study, including sustainability research in the fashion industry, development of size finding tools and returns prediction models, as well as Agent based approaches to customer behavior simulation in an online shop setting. Yang et al. (2017) show a comprehensive overview of the sustainability efforts and shortcomings in the fashion industry, touching on different topics ranging from the selection of sustainable materials to the effects of free returns and the lack of credibility of sustainability claims made by fashion companies. In the context of size recommendation, Eshel et al. (2021) propose a deep learning framework based on transformers for the size prediction across different clothing segments (Mens, Womens, Kids, Unisex clothing) and categories (Tops, Bottoms, Dress/Skirt, Footware). In addition, utilising the size predicting features for enhancing eBay's similar items recommendation service. Nestler et al. (2021) propose SizeFlags, a probabilistic Bayesian model based on weakly annotated large-scale data from customers for prediction of the most suitable size. In this study, the subjectivity of size perception is emphasised, stating that the 'true' size of a customer often remains unknown and can vary greatly by external factors including changes in physique over time and the mindset around what fits best.
When it comes to prediction of customer behavior, Hummel et al. (2011) present an Agent based simulation in order to predict customer behavior in an online shop setting when the preferred payment method is not available, taking into account gender specific preferences of payment methods from real-world data. Another recent study compares five different classical Machine Learning Algorithms for the predictions of returns, highlighting the importance of features representing bracketing behavior and ordering habits of customers (Niederlaender et al., 2024). Agent-based modeling can be used to simulate how targeting specific order behaviors, like size-related and selection-related returns, can influence shopping cart composition and ultimately impact broader factors such as material consumption, costs, and profits. This bottom-up approach allows for a detailed analysis of individual customer behavior and the effectiveness of prevention strategies. By incorporating real-world data and simulating customer interactions with size finding tools and targeted messages, this model can capture the heterogeneity of customer behavior and assess the sustainability implications of different strategies.

3 METHODS

This section presents the methods utilised for the estimation of achievable financial and environmental impact when employing strategies for the avoidance of returns and is composed of two steps. First, the data input, setup and output of the Agent-based simulation are described in subsection 3.1. Based on the output generated, financial aspects are analysed. An environmental analysis is conducted in the second step and the methodology for the determination of relevant parameters based on the output are described in subsection 3.2.

3.1 Simulation Setup

This simulation showcases three different return prevention strategies pertaining to selection orders, where a customer ordered multiples of the same clothing item in several sizes or a customer ordered multiple items from the same clothing category (for example dresses, pants, jackets). The latter case may

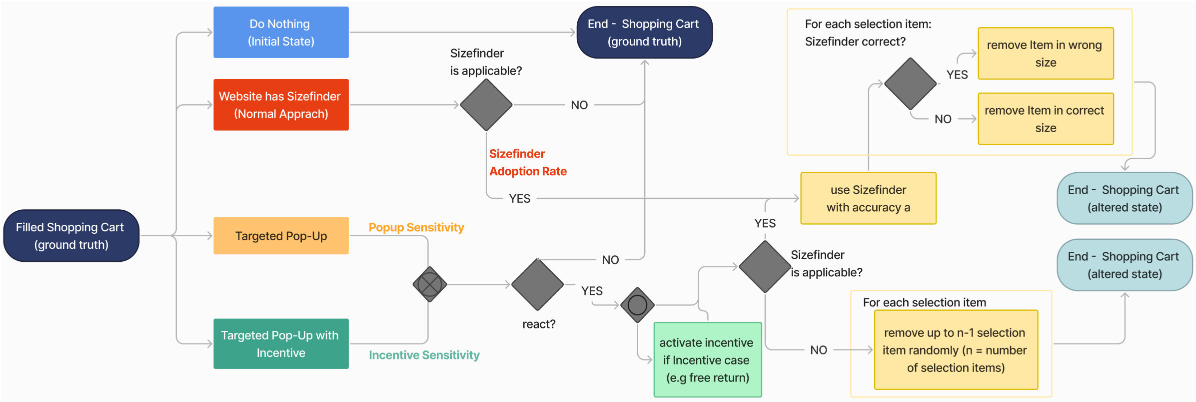

Figure 1: Flowchart representing the decision making process for each agent based on the initial shopping cart. Each of the four approaches (Initial, Normal, Targeted, Incentive) is simulated separately with the ground truth shopping cart data as a starting point.

not always indicate bracketing behavior, however, the dataset is a deciding factor.

The Input Data. This simulation is based on real-world sales and returns data of a German manufacturer of festive dresses and garments for special occasions. Therefore, the assumption that the majority of customers only intend to keep one festive garment from a category, one festive dress for example, is considered reasonable. The overall return rate of the shop is 72%, which may be caused by the specification on special occasions. The tabular data contains orders in the time span from March 1st 2023 to February 29 2024, where each order can be identified by a unique order ID. Further columns include the size of the items, a unique article ID, clothing category, the color, fit and style of the garment, but also the material composition in percent and the weight of the top layer fabric per square meter in grams. The latter two columns formed the basis for the calculations of material consumption, which in turn have been used in the environmental analysis. For items where the weight of the top layer fabric was not given a value, the average weight over all top layer fabrics was assigned. To estimate material consumption, for each clothing category the average square meters of total fabric needed, including multiple layers were estimated to be: Cocktail dress $3.0m^2$; Stola $1.0m^2$; Evening gown $4.5m^2$; Day dress $2.75m^2$; Dress $3.0m^2$; Jumpsuit $3.5m^2$; Bolero $1.25m^2$; Skirt (midi) $2.0m^2$; Top $1.25m^2$; Blouse $2.0m^2$; Corset $1.25m^2$; Skirt (long) $3.0m^2$; Pants $2.0m^2$; Jacket $2.25m^2$; Skirt (short) $1.25m^2$.
The weight of the fabric per square meter of fabric was approximated to match the given weight of the top layer fabric provided in the data. Due to the large amount of orders giving rise to averaging effects, the over- and underestimation of heavier or lighter garments were considered to be negligible. From the total weight estimation of the garment, subsequently the total amount of fabric components in the garments were estimated using the given material composition. Materials used as fabric components are given in Table 1.

Input Parameters. For each order in the real world data, an agent was created to act as an entity which alters the contents of the shopping basket as a result of the returns prevention strategies in place. Depending on the simulations scenarios, which are explained in the next paragraph, different input parameters drive the agents proneness to act a certain way. For the commonly known scenario where a size finding tool is in place but no active measures are taken, the Sizefinder Adoption Rate S_{normal} determines the probability with which a customer agent uses the size finding tool in a situation where they would place a size selection order instead in the ground truth shopping cart. For each agent, S_{normal} was drawn from a normal distribution with mean 0.2 and a standard deviation of 0.05, which makes some customer agents more prone to use the tool than others. The mean value and standard deviation for the Sizefinder Adoption Rate were determined by interviewing online fashion retailers which have their own size finding tool in place in their online shop. Based on this, an exemplary assessment of a person's Sensitivity to react to a targeted Popup due to the contents of their shopping basket indicating size or category selection orders was made. An increased proneness to react compared to the simple presence of a size finding tool is considered realistic, since it raises the awareness of the customer regarding their own shopping behavior. Therefore, the Targeted Popup Sensitivity S_{target} for each agent was drawn from a normal distribution with mean 0.4 and a standard deviation of 0.1. Similarly, a person's sensitivity to react to a version of the targeted popup which is not solely based on raising awareness but also on an incentive to act on the recommendations is considered to be even higher. Incentives might include offering free shipping or free returns in the case of ordering only what the size finding tool recommends. Thus, the Incentive Sensitivity $S_{incentive}$ for each agent was drawn from a normal distribution with mean 0.6 and a standard deviation of 0.1. The size finding tool was set to correctly suggest the best size for the customer in 80% of cases, so the accuracy a of the tool was set to be $a = 0.8$. To track the total costs present in the context of the shipping and return management, the cost for shipping a parcel (either as return or as shipping) were set to be EUR 5, where in the context of this simulation, the return cost is borne by the retailer, the outward shipping cost is borne by the customer. The costs for reprocessing an incoming return parcel were estimated to be EUR 10 on average, which is determined by the interviews conducted with online fashion retailers.

Simulation Scenarios. First, in order for the simulation results to generalise better, for each order three agents were created, which creates potentially different outcomes for each unique order. The observed scenarios are illustrated as a flow chart in Figure 1. Second, three separate strategies are simulated independently from each other and compared to the ground truth order data, which is shown as the 'Do Nothing' or 'Initial' state scenario. In the first strategy, the 'Normal' approach, the simulation is set up to mimick the prevention of size related selection orders due to the presence of a size finding tool on the website. The possible positive impact on non-selection orders due to better size estimation is not considered in this study, meaning that non-selection orders remain unaltered throughout the entire simulation. In the 'Normal' scenario, customer agents may or may not use the size finding tool depending on their personal preference determined by S_{normal}. Consequently, depending on the correctness of the tool in each particular case, determined by the sizefinder accuracy a, the customer agent may either keep one item in the correct size, or they may keep the item in the incorrect size.

The second returns prevention strategy, referred to as the 'Targeted' approach, the customer agent is made aware of the potential to use the size finder in the case of a size related selection in their shopping cart. In that case, they may or may not use the tool, depending on their sensitivity to such an awareness-raising strategy given by S_{target}. If the customer in turn has an order which can be classified as a selection order based on ordering $n \geq 2$ items from the same clothing category, the customer agent is also made aware of the potential returns caused and the effects that coincide with it. Depending on the customers sensitivity to the message S_{target}, the customer agent proceeds to remove up to $n-1$ items of this clothing category from the shopping cart. The third strategy is the same as the second, with a key difference: The agent is given an incentive to act according to the recommendations. The eagerness to react to the offering of an incentive like free returns or free shipping for each agent is given by their incentive sensitivity $S_{incentive}$.

Outputs and Implementation. The simulation was implemented completely using python with commonly used libraries like pandas and the Agent based modeling library Mesa. After each simulation scenario has been run, the potentially altered shopping cart including returns and non-returns are saved, as well as the total value of the cart and the value of the returned items in the cart. The information if the customer agent received any advantageous offer from the Incentive case is also saved as an output. The total amount of outward shippings and return shippings is tracked along with the total return processing cost.

3.2 Environmental Analysis

This chapter discusses the methodology used in this study to analyse the environmental impacts under different scenarios. Sustainability assessments are incomplete without consideration of environmental, one of the 3 pillars of sustainable development (European-Commission, 2024).The goal of this sustainability assessment is to explore how variations in material consumption across different scenarios impact the environment.

3.2.1 Methodology Selection

Life Cycle Assessment (LCA), a method commonly used in the literature to quantify the potential environmental impacts of a product system, was adopted. LCA involves four phases: Goal and Scope, Life Cycle Inventory (LCI), Life Cycle Impact Assessment (LCIA), and Interpretation. Since this study does not involve a complete LCA, it focuses solely on the potential environmental impacts of materials under different scenarios. Therefore, this study concentrates on two key phases of LCA: LCI and LCIA ISO 14040, ISO 14044).

As part of the LCI phase, environmental data related to raw materials is extracted from the LCI database, focusing on the environmental impact of fabrics during its production. In addition to categorising these data, the LCIA method is used to classify the impacts of different materials under various scenarios into specific impact categories. This categorization allows for a better understanding of the environmental impacts of each material under different scenarios. (ISO 14040, 2006)(ISO 14044, 2006)

3.2.2 LCI Database and LCIA Method

In LCA studies related to raw materials, there are variations in the selection of LCI databases across the literature. Table 1 presents different LCI databases and LCIA methods used in different studies that have conducted LCAs on the same type of fabrics as this study.

From Table 1, it is evident that the majority of relevant literature has selected the ecoinvent database, as their LCI database. Therefore, this study also chooses to use the ecoinvent database as the data source for analyzing the environmental impacts of different fabrics.

In contrast to the selection of LCI databases, there is a significant variation in the choice of LCIA methods among previous studies. These differences arise from variations in research locations and objectives. For example, IPCC primarily provides results for the Global Warming Potential (GWP) category (IPCC, 2022), while USEtox focuses on toxicity research in the United States and includes only categories related to toxicity (USEtox, 2024). Many articles have utilised the CML method, however, CML has not been updated since 2017 (Leiden-University, 2016). Given these uncertainties, this study has chosen to adopt the ReCiPe 2016 method, as it includes 18 midpoint categories and is continuously updated (ReCiPe, 2016).

3.2.3 Analysis of Environmental Impacts

As shown in Table 1, the variations in LCIA methods have also led to differences in the selection of impact categories by different authors. The ReCiPe 2016 method selected for this study encompasses various environmental impact pathways (ReCiPe, 2016). However, the environmental impacts of different fabric can vary significantly (Velden et al., 2014)(Parvez et al., 2018)(Wu, 2020)(Shena et al., 2010)(Guo et al., 2021)(Manteco, 2022)(Shuang et al., 2023)(Fangli et al., 2021)(Gomez-Campos et al., 2020)(Marek et al., 2023). To better demonstrate how changes in the ordering process can impact the environment from the perspective of fabric production and the 6 most relevant categories to the textile industry were selected for further focus. Carbon footprint (CC), Terrestrial Ecotoxicity (TEtox), and Human Toxicity (HT, both cancer and non-cancer) were selected because they are the Top 3 most frequently examined categories in other studies, as shown in Table 1. Additionally, Freshwater Ecotoxicity (FEtox) and Fossil Fuel Depletion were included. First, FEtox is consistently highlighted in EU article as one of the three major environmental issues in textile production, due to the large volumes of water pollution generated during the process (European-Parliament, 2024). Second, excessive fossil fuel consumption in fabric production contributes significantly to environmental degradation (Zaman et al., 2023). Reducing fossil fuel use has been identified as an important factor in making textile production more sustainable (Zaman et al., 2023).

This study will analyze how different scenarios of fabric usage affect six environmental impact categories. By identifying the fabric with the greatest environmental impact, this research will support sustainable decision-making.

Normen Clature Environmental Analysis. The Parameters for interpretation of environmental impacts are described by the following Normen Clature: AD: Abiotic depletion; AP: Acidification potential; AWARE: Available water remaining; CLCD: Chinese life cycle database; CC: Climate change; ET: Eutrophication; ETO: Ecotoxicity; EDIP: Environmental design of industrial products; FD: Fine dust; FPM: Fine particulate matter formation; FE: Freshwater eutrophication; FEtox: Freshwater ecotoxicity; GWP: Global warming potential; HT: Human toxicity; HTc: Human toxicity, cancer; HTnc: Human toxicity, non-cancer; IPCC: International panel on climate change; IR: Ionising radiation; LU: Land use; ME: Marine eutrophication; MEtox: Marine ecotoxicity, RD: Mineral, fossil and renewable resource depletion; OD: Ozone depletion; OF: Ozone formation; OFh: Ozone formation, Human health; PM: Particulate matter; POF: Photochemical ozone formation; POxF: Photochemical oxidant formation; PED: Primary energy demand; SOD: Stratospheric ozone depletion; TA: Terrestrial acidification; TE: Terrestrial ecosystems; TEtox: Terrestrial ecotoxicity; WU: Resource depletion-water; USEtox: United nation environment program and society of environmental toxicology chemistry; WC: Water consumption

Table 1: Summary of LCI databases and LCIA methods used with impact categories from various literature sources.

Material type	LCI database	LCIA method	Impact categories	References
Nylon	Ecoinvent	IPCC, USEtox, ReCiPe, IMPACT 2002+, CML, Ecopoints 97, Eco-indicator 99, Green-house gas protocol	GWP, ETO, AP, ET, POxF, FD, TE, FE, SOD, IR, OFh, FPM, OF, TA, MEtox, HTc, HTnc, LU, WC	(Velden et al., 2014)(Parvez et al., 2018)
Polyester	Gabi, Ecoinvent	EDIP, IPCC, USE-tox, ReCiPe, IMPACT 2002+, CML	GWP, WC, ETO, AP, ET, POxF, FD, AD, OD, HT, FEtox, Tetox	(Velden et al., 2014) (Wu, 2020) (Shena et al., 2010)
Elastane	Ecoinvent	IPCC, USEtox, ReCiPe,IMPACT 2002+	GWP, ETO, AP, ET, POxF, FD, MEtox; WC	(Velden et al., 2014)
Viscos	CLCD, Ecoinvent	CML, IPCC	AD, PED, WU, AP, GWP, ET, CC, OD, HT, FEtox, Tetox, POxF, AP	(Shena et al., 2010) (Guo et al., 2021) (Manteco, 2022)
Cotton	Ecoinvent	CML, IMPACT 2002+, ReCiPe, EDIP, USEtox, Eco indicator 99, foot-print, Australian impact method, Australian Indi-cator Set V3, IPCC	CC, OD, TA, FE, FE-tox, HT, WC, AD, Tetox, POxF, AP, ET	(Shena et al., 2010) (Manteco, 2022) (Shuang et al., 2023) (Fangli et al., 2021)
Flax	Ecoinvent, Agribalse	ILCD 2001+	CC, OZ, PM, IR, POF, AP, FE, ME, RD	(Gomez-Campos et al., 2020)
Metallic fab-rics	Ecoinvent	IPCC, USEtox 2, AWARE	GWP, HTc, HTnc, FE-tox, WC	(Marek et al., 2023)

4 DISCUSSION OF RESULTS

4.1 Comparison of the Simulation Outcomes

The relative changes in the simulation outcomes compared to the initial ground truth case are summarised in Table 2. The absolute values are compared in Figure 2. It becomes clear that the difference between the targeted approach and the normal approach is not very pronounced. The normal approach often saves more resources than the targeted approach, despite the latter's broader scope. While the targeted approach reduces total returns, it also decreases the number of items kept. The incentive approach, while effective in reducing returns, might impact sales. Additional costs associated with incentives should be considered. While the overall reduction in material consumption is similar across cases, it's not directly proportional to the reduction in returns. This is due to varying product compositions and return reasons. Further research is needed to optimize pop-up timing and placement, as well as address complex cases involving multiple high-risk items. Due to the high individuality of the carts as well as the unknown sensitivity of customers to small changes in size und unknown personal preferences, the decision process of customers remain pre-dominantly difficult to comprehend. Online retailers are therefore encouraged to explore their customers sensitivities S_{normal}, S_{target} and $S_{incentive}$ in the context of their own online shop. Further, the sensitivities S_{target} and $S_{incentive}$ may vary depending on the return category, for example making customers on aver-

Table 2: Relative changes of the different scenarios (N = Normal, T = Targeted, I = Incentive) compared to the initial scenario.

Outcome	N [%]	T [%]	I [%]
Total Returns	-0.67	-0.69	-9.14
Total Non Returns	-1.93	-1.84	-10.4
Return Shippings	-0.20	-0.17	-1.90
Outward Shippings	-0.24	-0.23	-0.72
Sum Price Returns	-0.67	-0.71	-9.46
Sum Price Non Returns	-2.01	-1.97	-11.1
Return Shipping Costs	-0.20	-0.17	-1.90
Total Outward Shipping Costs	-0.24	-0.23	-0.72
Return Processing Costs	-0.67	-0.69	-9.14
Nylon	-0.79	-1.59	-5.90
Polyester	-1.12	-1.06	-9.68
Metallic Fabric	-0.93	-0.95	-6.16
Elastane	-1.23	-1.16	-8.75
Viscose	-0.83	-1.37	-4.41
Cotton	-1.18	-1.49	-11.3
Flax	-0.92	0.00	-1.84

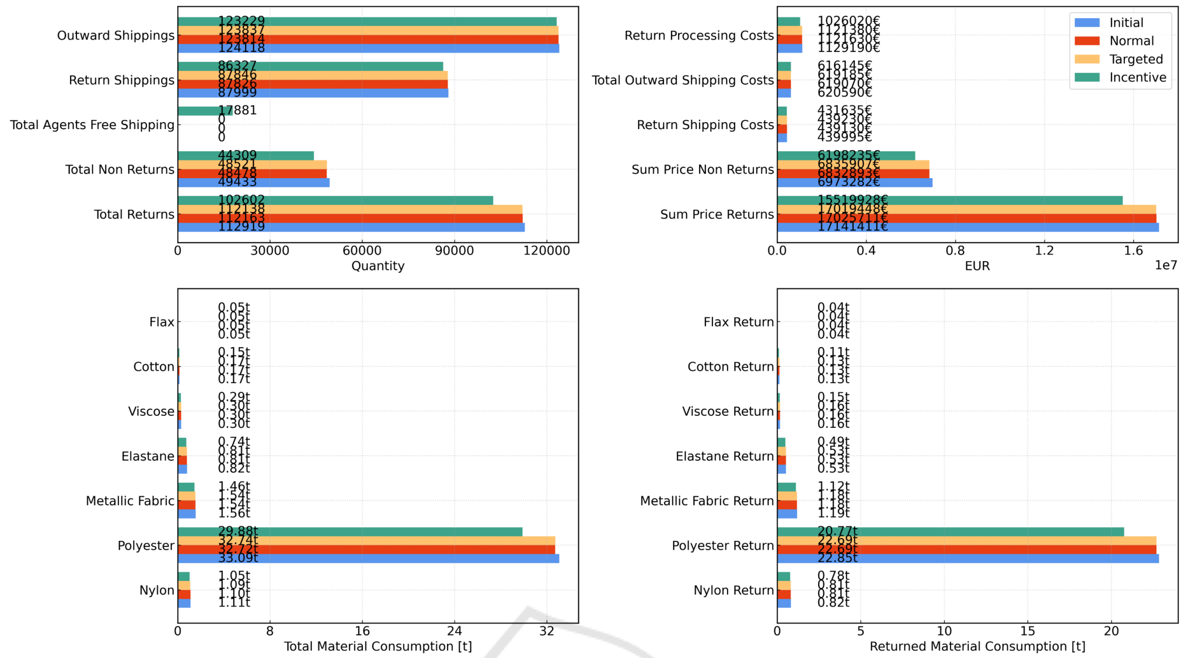

Figure 2: Comparison of simulation outcomes for the four scenarios, where Initial represents the ground truth data.

age more susceptible to removing size selection items than removing category selection items. This differentiation needs further investigation.

4.2 Impact of Outcomes on Relevant Environmental Parameters

A key objective of this research is to provide an assessment and classification of potential environmental impacts that may arise due to changes in the ordering process. For this reason, the results from the various scenarios in Figure 4 were analysed for their environmental impacts using the environmental analysis method described (see subsection 3.2). As outlined in the methodology, the focus was placed on the following six impact categories: Climate Change (CC), Freshwater Aquatic Ecotoxicity (FAE), Terrestrial Ecotoxicity (TE), Human Toxicity, cancer (HTC), Human Toxicity, non-cancer (HTNC), Fossil Depletion (FT). The results are presented in two main sections. An overview of the absolute values in the scenarios is described. Then the relative share of the individual materials for the respective impact category is discussed in more detail and it is described whether there are changes in the scenarios compared to the “Initial” scenario.

4.2.1 Absolute Summed Impacts per Scenario

Figure 3 illustrates the impact of the different clothing sales scenarios (Initial, Targeted, Incentive, and

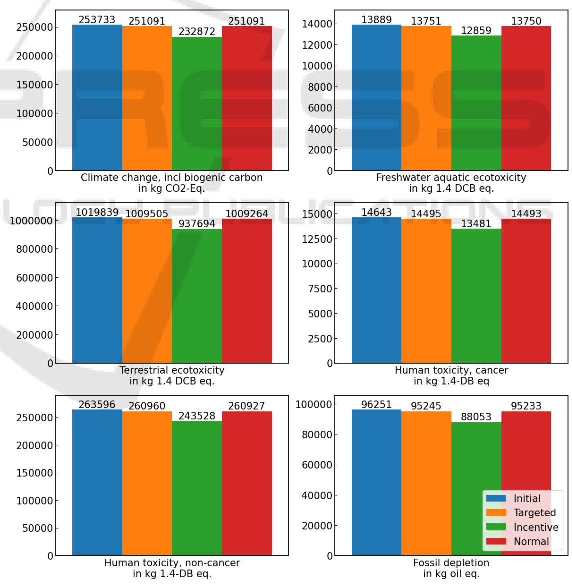

Figure 3: Absolute values of different impact metrics for different ordering scenarios.

Normal) on the six environmental metrics. The units are not the same for all metrics. Care should therefore be taken when comparing values across metrics. The chart highlights the significant impact that different sales strategies can have on the environment. Outcomes for other metrics are shown in the Appendix. The ”Incentive” scenario consistently outperforms the others across all six metrics, indicating that it is the most sustainable option. The percentage decline in each metric is between 7 and 9 percent. The highest percentage decrease is in Fossil depletion with 8.6 percent and the lowest in Freshwater aquatic ecotoxicity with 7.5 percent.The Target scenario also lowers the impact compared to Normal and Initial. The highest decrease compared to the Initial Scenario is in Fossil depletion with 1.2 percent and the lowest Freshwater aquatic ecotoxicity with one percent. The CO2 equivalent can be considered in more detail as an example. The difference between the initial scenario with 253 tons and the incentive scenario with 232 tons corresponds to savings of 21 tons. By way of comparison, a return flight of 3000 miles (e.g. from Boston to London and back) emits around one ton of CO2 per passenger(United States Environmental Protection Agency, 2018). Freshwater aquatic ecotoxicity has about a ton of difference between Initial with 13t and Incentive with 12t 1.4 DCB equivalent. The target of a maximum pollutant concentration of 75 micrograms of p-DCB per liter of drinking water set by the United States Environmental Protection Agency (2009) (EPA) can be used for reference. Both examples were used to better illustrate the quantities given. Overall, it can be seen that, compared to the initial scenario, only the incentive scenario has a clear influence and would have an impact reduction of around 8 percent in most impact categories. Target and Normal also show a reduction in the impact categories, but this is significantly smaller.

4.2.2 Relative Proportion of Individual Materials per Impact Category

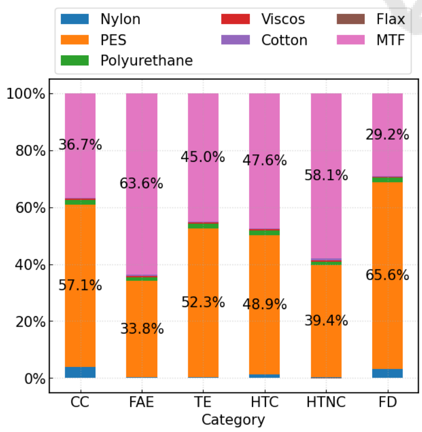

Figure 4: Percentage share of the analysed fabrics of the total impact in the various metrics.

Figure 4 illustrates the relative impact of different fabric materials on the same six environmental metrics as in Figure 3. The values are totaled over the 4 scenarios. The material composition of the clothes significantly influences the environmental footprint. The use of PES (Polyester) and MFT (Metallic Fiber) consistently contributes to a higher impact across all metrics compared to other fabrics, despite the fact that the total consumption of MFT is just a small share of the total material consumption. PES with percentages between 65 and 33 and MTF between 63 and 29 percent. Nylon and Polyurethane generally exhibit lower environmental impacts. Viscos, Cotton and Flax demonstrate the lowest impacts relatively. This analysis highlights the significance of fabric composition in sustainable clothing consumption. While interventions in the ordering process can have a positive impact, substantial improvements require more significant changes. Focusing on PES and MFT components offers the greatest potential for reducing environmental impact.

5 CONCLUSION AND OUTLOOK

This work proposed an Agent-Based approach for the estimation of financial and environmental outcomes when implementing return prevention strategies in fashion e-commerce. Alternative order outcomes when targeting customers based on size or category related selection orders and intervening with targeted popups or incentives were explored and compared to ground truth order data from a German online retailer, as well as the scenario of a size finding tool in place but not raising awareness about its presence. Depending on customers unique sensitivity to these strategies, returns can be prevented by reducing selection orders, having a positive financial impact through saved return shipping and processing cost, but also preventing some amount of orders that would have not been returned in the initial scenario. However, this aspect needs further investigation taking into account the possibility of follow-up orders after returning the first time. One key objective of this work is to classify the sustainability effects that could arise as a result of changes in the ordering process. For this reason, the sustainability effects of the results from the various scenarios from Figure 4. were examined using the sustainability analysis method described in subsection 3.2. In a first step, the impact of the outcome from the initial scenario was determined. In a second step, the initial scenario was compared with the changed outcomes of the different scenarios, which were also evaluated with regard to their sustainability effects. In a third step, these sustainability assessments are used to compare the various impacts of the scenarios. Future work is suggested to investigate the impact of targeting other return types besides selection order induced returns, while taking varying sensitivities dependent on the return type into account. The potential for cart abandonment should be considered. Real-world customer responses to these strategies must be studied. Online retailers are encouraged to analyze their own sales and return data to estimate the potential impact on financial and environmental sustainability. Expanding these strategies to other e-commerce types could offer new insights. AI and ML can help predict returns and inform decision-making for efficient and sustainable return processing. A return prediction system could identify high-risk orders and items, enabling targeted interventions to prevent returns. By analyzing customer return history, personalized recommendations can be made to reduce returns without discouraging legitimate ones.

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APPENDIX

Table 3: Outcomes of Initial and Normal impact metrics for different ordering scenarios.

Category	Initial	Normal	Unit
Climate change incl biogenic carbon	253733.28	251091.32	kg CO2-Eq.
Freshwater aquatic ecotoxicity	13889.52	13750.29	kg 1.4 DCB eq.
Marine aquatic ecotoxicity	18070.87	17889.51	kg 1.4 DCB eq.
Terrestrial eco-toxicity	1019839.03	1009264.53	kg 1.4 DCB eq.
Freshwater Eutrophication	125.70	124.46	kg P eq.
Marine Eutrophication	45.70	45.23	kg N eq.
Terrestrial Acidification	695.41	688.14	kg SO2 eq.
Photochemical Ozone Formation. Ecosystems	565.56	559.55	kg NOx eq.
Ionizing Radiation	21460.72	21245.99	kBq Co-60 eq.
Human toxicity cancer	14643.98	14493.22	kg 1.4-DB eq.
Human toxicity non-cancer	263596.40	260927.14	kg 1.4-DB eq.
Fine Particulate Matter Formation	301.25	298.08	kg PM2.5 eq.
Photochemical Ozone Formation. Human Health	518.20	512.70	kg NOx eq.

Table 3: Outcomes of Initial and Normal impact metrics for different ordering scenarios (cont.).

Category	Initial	Normal	Unit
Stratospheric Ozone Depletion	0.784	0.775	kg CFC-11 eq.
Land use	4984.98	4932.55	Annual crop eq.
Fossil depletion	96251.62	95233.25	kg oil eq.
Metal depletion	2748.16	2720.18	kg Cu eq.
Freshwater Consumption	3667.45	3628.48	m3

Table 4: Outcomes of Targeted and Incentive impact metrics for different ordering scenarios.

Category	Targeted	Incentive	Unit
Climate change incl biogenic carbon	251091.30	232872.84	kg CO2-Eq.
Freshwater aquatic ecotoxicity	13751.61	12859.24	kg 1.4 DCB eq.
Marine aquatic ecotoxicity	17891.43	16726.44	kg 1.4 DCB eq.
Terrestrial eco-toxicity	1009505.05	937694.95	kg 1.4 DCB eq.
Freshwater Eutrophication	124.46	116.57	kg P eq.
Marine Eutrophication	45.20	42.06	kg N eq.
Terrestrial Acidification	688.10	637.73	kg SO2 eq.
Photochemical Ozone Formation. Ecosystems	559.62	516.92	kg NOx eq.
Ionizing Radiation	21248.71	19875.78	kBq Co-60 eq.
Human toxicity cancer	14495.31	13481.50	kg 1.4-DB eq.
Human toxicity non-cancer	260960.88	243528.13	kg 1.4-DB eq.
Fine Particulate Matter Formation	298.10	275.83	kg PM2.5 eq.
Photochemical Ozone Formation. Human Health	512.76	473.89	kg NOx eq.
Stratospheric Ozone Depletion	0.776	0.710	kg CFC-11 eq.
Land use	4929.10	4564.97	Annual crop eq.
Fossil depletion	95245.71	88053.60	kg oil eq.
Metal depletion	2719.68	2536.61	kg Cu eq.
Freshwater Consumption	3625.23	3347.68	m3