Advances in AI-Based Garment Returns Prediction and Processing: A Conceptual Approach for an AI-Based Recommender System

Soeren Gry[a], Marie Niederlaender[b], Aena Nuzhat Lodi, Marcel Mutz[c] and Dirk Werth[d]
August-Wilhelm Scheer Institut, Uni Campus D 51, Saarbrücken, Germany
{firstname.lastname}@aws-institut.de

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Abstract: The ever-increasing volume of returned garments not only represents a huge increase in costs for retailers or manufacturers and an inventory risk that is difficult to calculate, but also has a high environmental impact due to the destruction of the garments and the necessary logistics processes. Most of the existing solutions to these problems aim to eliminate returns altogether. However, many returns cannot be avoided, e.g. orders for a selection of products, repairs or quality-related returns. For this reason, this study explores the potential of AI to predict returns and make recommendations on how best to plan the reverse logistics network, resulting in environmental and economic benefits. To this end, an extensive literature review was conducted to capture the current state of research. Based on this, a conceptual approach for the development of an AI-based recommender system for the best possible handling of returns will be derived.

1 INTRODUCTION

During the corona pandemic, the share of global e-commerce rose from 15% of total retail sales in 2019 to 21% in 2021. For 2022, a share of 22% of total retail sales is expected. As a result, e-commerce growth has slowed but remains high and is expected to increase from $3.3 trillion in 2022 to $5.4 trillion in 2026 (Morgan Stanley, 2022). The volume of transport and product returns increases accordingly. While e-commerce has significant advantages for consumers over bricks-and-mortar stores, and not just during a global pandemic, there are also some disadvantages. E-commerce does not allow consumers to see, feel or try products before they buy them. Returns are therefore inevitable (Asdecker and Karl, 2018). In a European comparison, Germany has the highest number of parcel returns. Around 24% of parcels in Germany are returned by consumers. In 2021, around 530 million returns involving 1.3 billion items were made in Germany. 91% of returned items were apparel and shoes. As well as the economic harm caused by the difficulty of achieving positive margins on e-commerce, the environmental consequences of this ordering behaviour are also significant. An estimated 795,000 tonnes of CO2 are caused by returns in Germany alone, the equivalent of 5.3 billion car kilometres (Forschungsgruppe Retourenmanagement, 2022). Returns are one reason why the fashion and apparel industry is responsible for 5% of global emissions, more than international air travel and cruise ships combined. This makes the fashion and apparel industry one of the top three polluters and puts it at the centre of policy efforts (Vogue/BCG, 2021). The consumer behaviour described in relation to returns is not only observed in Germany, where up to 60% of apparel and shoes are returned, but is also almost congruent at European level (Forschungsgruppe Retourenmanagement, 2022). Manufacturers and retailers take preventive and reactive approaches to dealing with returns (Deges, 2021). This study looks at current reactive approaches to reducing the environmental and economic costs of returns. In order to handle returns in the best possible way and to recycle them in the sense of second life planning, manufacturers and retailers depend on accurate forecasts of the volume of returns. In this context, Artificial Intelligence (AI), and in particular Machine Learning (ML) as part of AI research, can be used to recognise patterns and regularities in huge data sets (Lickert et al., 2021; Schwaiger and Steinwendner, 2019). This research paper examines current scientific approaches to

[a] https://orcid.org/0000-0002-4441-0517
[b] https://orcid.org/0009-0008-1935-821X
[c] https://orcid.org/0000-0002-5918-6407
[d] https://orcid.org/0000-0003-2115-6955

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1) predicting returns and 2) providing them with the best possible processing. The focus of this paper is on AI-based approaches and the identification of current research gaps. At the same time, priority is given to literature focused on the fashion and apparel sector due to the high environmental impact of this industry. The structure of the research paper is as follows. First, AI-based approaches are explored to predict returns, return quantities and reasons for returns. Secondly, the AI-based processing of returns within the reverse logistics process is investigated, with the aim of enabling economically and ecologically sensible further processing. All findings from these sections are summarised in Table 1. Then the paper discusses the use of an AI-based recommender system that can be part of reverse logistics planning. The final section summarises the findings, including identified research gaps, and provides an outlook.

2 METHODOLOGY

This paper aims to give an overview of the most recent practices and innovations in the area of return management with a focus on the fashion and apparel industry, covering the topics (Figure 1):

1. Returns Forecasting and Consumer Returns Behavior
2. Reverse Logistics Network Design and Optimisation (including Returns Management)

The literature review focused primarily on the five-year period between 2018 and 2022, and was conducted between October 2022 and February 2023. For that matter Google Scholar, Wiley Online Library, ScienceDirect and Springer Link were searched, including snowballing techniques to include relevant older sources outside our primary search period. This paper represents an overview of the most relevant developments in the fashion and apparel industry with a roadmap for future research, it does not aim to provide a systematic review on return management. The following search keywords were used for Topic 1: Returns Forecasting, Product Return Prediction, Consumer Return Behavior, Prediction of Consumer Returns; and for Topic 2: Reverse Logistics Network Design, Reverse Logistics Network optimisation, Reverse Logistics, Returns Management and for Context: Sustainability, AI, Artificial Intelligence, Machine Learning, Fashion, Apparel, Online Retail, E-Commerce. New or particularly relevant publications that relate to, or could be translated into, the fashion and apparel industry were selected.

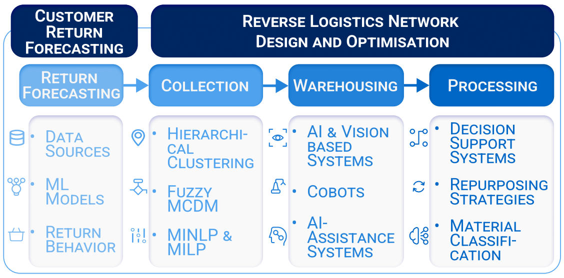

Figure 1: Structure of topics along the supply chain with top-down increasing detail level.

3 LITERATURE REVIEW

3.1 On Return Forecasting and Observations of Return Behavior

3.1.1 Comparison of Machine Learning Methodologies

Mathematical models have been proven to be difficult to establish in multi-parameter and multi-variable problems (Tüylü and Eroğlu, 2019). A problem such as prediction of returns can have many possible factors, and so in order to explore all such possibilities, many recent studies have covered a variety of techniques and implications regarding the use of ML methods to forecast returns in fashion and apparel markets.

A Preliminary Selection of Algorithms: Tüylü and Eroğlu (2019) performed one such analysis and comparison of different ML methods to estimate a demand forecast, which they were then able to extrapolate into an estimate of product returns. Their experiment took into account algorithms in four distinct categories: lazy, rule-based, decision tree, and functional. The dataset consisted of information on fashion and apparel products, primarily women's trousers. The highest levels of accuracy obtained on this large dataset were consistently achieved by the M5P decision tree algorithm, which combines the underlying principles behind multiple linear regression and decision trees for data mining (Quinlan et al., 1992). Besides this, among the functional algorithms, linear regression and support vector regression also proved to be a good fit for the problem, whereas multilayer perception did not perform as well as the others. Both of the evaluated rule-based algorithms, M5Rules and Decision Table, demonstrated comparable performance as well. M5Rules has the ability to make predictions for nominal and numerical quantities, by selecting the most effective rule generated in each cycle of tree creation (Holmes et al., 1999).

Simple Data Mining Methods: In the study by Asdecker and Karl (2018), the performances of simple and complex data analysis methods for the purpose of predicting consumer returns were compared and contrasted, to determine whether or not the use of complex methods is required to predict returns by customers. Instead of customer information such as order and return history or shopping basket composition, they were able to make use of shipment and returns information. It was shown that even the simplest methods such as binary logistic regression and linear discriminant analysis did not lag so far behind more complex methods such as ensembles, helping retailers to identify the variables that contribute to product returns. Return probability was found to be positively correlated with: the total value of the shipped goods within a package, the number of items in a shipment, and the age of the account that the consumer used to order the products; and negatively correlated with the delivery time. The authors also found that packages delivered to women have the highest probability of being returned.

Feature Extraction for Large Sparse Datasets: In order to create high-quality ML models that produce accurate return forecasts, large datasets with informative features are absolutely crucial. Urbanke et al. (2015) presented Mahalanobis feature extraction, their newly developed method to reduce dimensionality of large-scale sparse datasets whilst retaining useful information from the dataset. The authors carried out their experiment on a dataset from a leading fashion retailer in Germany that had a returns rate of 57.3%. Using a sparse matrix format, the memory requirement of the dataset was reduced by more than 99%. Mahalanobis feature extraction outperformed all of the seven other feature extraction methods that it was compared with in the study, demonstrating its utility with regards to such datasets. Besides this, the combination of Mahalanobis feature extraction and adaptive boosting was also outperforming against logistic regression and linear kernel support vector machine. The hybrid method was able to predict the sales which had a very high probability of being returned. Further work on such an approach may prove fruitful in efficiently and accurately processing returns data for predictions.

Time-Series Model: Return forecasting is essentially a time-based problem, and so, a model based on time-series or lagged sales may be a good fit. Shang et al. (2020) explore this perspective, showing that such models may indeed decrease the prediction error by up to 18% with the right configurations. The predictions were made using a predict-aggregate approach on data from an online jewelry retailer, that formally accepted returns within 30 days after purchase, but also did not often reject late returns. Overall, the lagged sales regression model outperformed the time-series based ARIMA model (Jenkins, 1970) in most of the categories that were measured.

3.1.2 Findings Regarding Return Behaviour

Returns occur due to many reasons, including but not limited to impulse buying due to sales or promotions, mismatch with expectations, or intentionally, when the customer orders a larger set of items than they plan to retain. The following section describes the findings in literature pertaining to return forecasting using ML techniques, mainly in the industry of fashion and apparel.

Demographics and Return Rates: Makkonen et al. (2021) explored the implications of consumer demographics and preferences in payment methods on product returns made by online consumers. The authors collected data via a questionnaire aimed at online consumers in Finland, asking the participants about their gender, age, education and income, along with their payment method preference, and return behaviour. Using this information, a three-part analysis of the data was carried out. Firstly, the product return frequency was correlated using cumulative odds ordinal logistic regression. Secondly, the reasons for returning items stated by participants were categorised via content analysis. Thirdly, specific product return reasons were learned using binomial logistic regression. Returns were found to be made more often by women, younger people, and people who preferred to pay via invoice. 12 participants, of whom most were in their 20s, brought up the custom of bracketing. Bracketing refers to the purchasing of multiple items, typically within the same order, with the intention of keeping only a subset of them and returning all the rest. Bracketing is most commonly carried out with fashion items, primarily apparel and shoes (Bimschleger et al., 2019). When analysing the reasons for product returns, the authors observed that over 60% of responses cited returning clothes and shoes due to wrong size or bad fitting, and also that these returns were most often made by women. On the other hand, returns made due to a faulty or damaged product were mostly returned by men, and also by people who very rarely return products (less than yearly). People who return products as frequently as returning monthly were much more likely to state that they returned products due to a mismatch with their own expectations of the items.

Consumer Behaviour Leading to Returns: Reasons for consumer returns have also been closely examined by Asdecker et al. (2017), with the use of linear and logistic regression using data from a German online shop dealing mainly in women's apparel. This study included information on customers' shopping baskets, order and return history, as well as payment method, coupons, and whether or not a free gift was included for each order. This study finds more specific correlations with regards to bracketing. Another such distinct and perhaps unexpected finding is that ordering the same item in multiple colours in fact lowers the return rate. The higher the average product price of the order, the higher the likelihood of a return. Paying for an order by invoice also increases the chance of a return, similar to the finding by Makkonen et al. (2021) regarding payment method preference. Returns were also found to be associated with the use of coupons, which may cause customers to make risky purchases on impulse. Including a free gift in the package was also found to reduce the probability of a return from such an order. Lastly, the greatest impact was found using the historical returns information pertaining to each article and each customer. Both of these return rates are directly proportional to the probability of the return of an item by a customer, providing the most information to the predictive model.

Pricing and Product Reviews: Sahoo et al. (2018) have found that apparel products with a lesser number of reviews increase the likelihood of bracketing by customers. When products sold online have multiple unbiased reviews from customers, their return rate lessens. Unbiased ratings mean that there are no incorrect ratings or, for example, conflicts of interest on the part of the raters. Conversely, biased reviews on a product are associated with increased return rates. They also found that expensive items are less likely to be returned, probably because the customer has put more mental effort into considering their decision before making the purchase. The approach adopted by the authors makes use of an analytical model which they propose, and a two-stage Probit model, a type of binary regression model (Heckman, 1979), to approximate the effect of product reviews on purchases as well as returns.

Shipping Practises: Free shipping promotions have been shown to positively influence spending on products that are difficult for customers to assess, which in turn increases the return rate (Shehu et al., 2020). It is important to note that this does not include free shipping policies. Shehu et al. (2020) explain that customers view such promotions as compensation for possible returns. The study makes use of a Type II tobit model, in which some part of the target variable is obscured (Van Heerde et al., 2005).

Additionally, many online retailers offer free shipping when a customer's order value reaches a certain threshold, and such free shipping policies have been shown to lead to a greater return rate (Lepthien and Clement, 2019). The study was performed in collaboration with a retailer of streetwear and sportswear items, and the aforementioned results were obtained using OLS and logistic regressions.

Payment Methods, Assortment Diversity and Historical Records: In the Business-to-Business (B2B) domain, whilst manufacturers have the statistics for the returns that they receive from retailers' leftover stock after the end of a season, they may not necessarily have access to valuable customer returns data from the retailer, which could in fact help them to reduce the number of B2B returns. Yan and Cao (2017) used data shared by an online retailer with the manufacturer of its products, which consisted of shoes, apparel, and accessories to gain insights. Firstly, it was found that the payment method used by the customer was a helpful predictor of product returns: credit cards, encouraging a 'buy-now-pay-later' mindset leading to impulsive and low-effort purchases, were found to be associated with a high return rate. On the other hand, paying by cash was found to curb consumers' impulsive urges to make unnecessary purchases, and was associated with a low return rate. Secondly, if the assortment of apparel, footwear, and accessory items ordered by the customer is very diverse results on lower return rates. Therefore it is very important to distinguish between bracketing and simply buying many items at once to keep. Lastly, the return rate was also found to be inversely proportional to the number of items that the customer had ordered from the online retailer in the past. This study strongly reinforces the importance of B2C-level information for predicting returns.

Our literature search did not identify any AI or non-AI based approach that addresses a recommender system to provide guidance on how best to handle returned items. Predicting returns provides the basis for handling returned items in the best possible way and tailoring reverse logistics processes accordingly.

3.2 On Reverse Logistics Network Design and Optimisation

Reverse logistics is defined as "the process of moving goods from their typical final destination for the purpose of capturing value or ensuring proper disposal" (Chileshe et al., 2016). Reverse logistics planning is

Table 1: Overview of literature for each research topic, sorted by subcategory and approach.

Topic	Subcategory	Approaches	Literature
Consumer Returns Forecasting	Comparison of Machine Learning Methods	Tree-based models, lazy, rule-based, functional algorithms	Tüylü and Eroğlu (2019)
		Data mining methods	Asdecker and Karl (2018)
		Mahalanobis feature extraction	Urbanke et al. (2015)
		Time-series based model	Shang et al. (2020)
	Observations of Consumer Behavior	Subject to demographics, payment method preference, bracketing	Makkonen et al. (2021); Asdecker et al. (2017)
		Effect of pricing, effect of accuracy and availability of product reviews	Sahoo et al. (2018)
		Free shipping promotions, threshold-based free shipping policies	Shehu et al. (2020); Lepthien and Clement (2019)
		Effects of payment methods, assortment diversity, and past customer records	Yan and Cao (2017)
Reverse Logistics Network Design	Digital Reverse Logistics Twin	Real-time data, smart robots and AI-based data predictions (e.g. for vehicle routing)	Ivanov and Dolgui (2021); Zhang et al. (2018); Sun et al. (2022a,b)
	Mathematical Programming	Mixed linear programming (MILP) (e.g. facility location-allocation)	Das et al. (2020)
		Hybrid multicriteria decision-making (MCDM) (e.g. selection of 3PRLP)	Wang et al. (2021)
Collection	Machine Learning	Hierarchical Clustering for facility location-allocation	Lin et al. (2021); Nanayakkara et al. (2022)
	Mathematical Programming	Fuzzy MCDM for collection optimisation	Sagnak et al. (2021); Ocampo et al. (2019)
		Fuzzy MONLP green vehicle routing	Soleimani et al. (2017)
		MINLP facility location-allocation	Vahdani et al. (2012)
Warehousing	AI- and Vision-based Systems	AI- and vision-based identification, inspection and sorting in combination with smart robots	Wang et al. (2020); Zhang et al. (2018)
		Cobots and AI-based systems for automatic sorting	Sarc et al. (2019)
Processing	Remanufacturing	RFID, Chaos-based Interactive Artificial Bee Colony (CI-ABC)	Kumar et al. (2015)
	Textile Recycling	Artificial Neural Networks (ANN)	Furferi and Governi (2008)
		Zero-waste, second hand clothing	Lewis et al. (2017)
		Design for improved recycling	Durham et al. (2015)
		Textile to textile: drivers & inhibiters	Sandvik and Stubbs (2019)
		Recycling and reuse of clothing in general	Xie et al. (2021)

more difficult than forward logistics because there is great uncertainty about the quantity, timing and quality of the returned products (Flapper, 1995). The ability to more accurately predict the timing and volume of returns using AI-based predictions is essential for optimising the reverse logistics process. This enables optimal performance in terms of collection, transportation, remanufacturing and recycling (Tibben-Lembke and Rogers, 2002). Forecasting returns is therefore important for the design of the reverse logistics network and the planning and control of the recovery processes (Xiaofeng and Tijun, 2009). Based on Agrawal et al. (2015) and Wilson et al. (2021), this research paper distinguishes four main activities within the reverse logistics process that are also relevant to the fashion and apparel industry: network design, collection, warehousing and processing. In the context of the following, this research paper will examine the contribution that AI makes, or can make, to the four components of reverse logistics.

3.2.1 Network Design in Reverse Logistics

Network design is a strategic consideration for all reverse logistics functions. Managers need to decide at a strategic level how the reverse logistics infrastructure should be structured in general. This includes, for example, the number and geographical location of logistics sites and the organisation of transport between them. There are many differences between reverse and forward logistics, which is why reverse logistics cannot simply copy the process of forward logistics. When goods are returned to the manufacturer, they are sent from many, initially unknown, points to a central location and vary greatly in quality (Wilson et al., 2021). This lack of visibility and apparent unpredictability can be addressed with AI-based and non-AI-based approaches discussed in the previous sections of this paper.

Using AI in Network Design: AI and real-time data integration are often seen as the basis for making strategic, tactical and operational decisions regarding a smart and sustainable reverse logistics network design (Sun et al., 2022b). In combination with mathematical models and computer-aided simulations, AI-based data predictions and real-time data can be used to build a digital reverse logistics twin in the sense of Reverse Logistics 4.0 (Ivanov and Dolgui, 2021). This can then be used to make informed decisions about the design of the reverse logistics network by reducing uncertainties and, for example, planning optimal scheduling and vehicle routing (Zhang et al., 2018). Reasonable decision parameters for vehicle routing could be, for example, economic costs, truck utilisation, greenhouse gas reduction and truck driver working hours (Sun et al., 2022b). Developing an intelligent digital reverse logistics twin to inform network design decisions requires deep methodological integration and system integration, including smart robots and devices, analytical models, visualisation tools, etc., which must be effectively and seamlessly linked (Sun et al., 2022a).

Mathematical Methods and Network Design: According to the current state of research, the selection of third-party reverse logistics providers (3PRLP) is not based on AI, but rather on mathematical models. Wang et al. (2021) use a hybrid multicriteria decision making (MCDM) approach (FAHP combined with FTOPSIS) to improve 3PRLP evaluation and selection practices for several industries and to address the increasing demand for outsourcing reverse logistics activities. In their empirical case study focusing on a fashion retailer, Das et al. (2020) investigate which locations are best suited for initial collection centres (ICCs), where customer returns are stored for some time before being sent to final warehouses. They used Mixed Linear Programming (MILP) as an approach to minimise the costs (environmental and economic) of the reverse logistics network.

3.2.2 Collection Approaches Including AI Methods

For the creation of a sustainable reverse logistics network, it is essential to optimise the routes the returned goods take to their next destination to either be repaired, resold, reused, remanufactured or recycled (Alkahtani et al., 2021). This gives rise to the question of how and where to collect the goods, which in many cases can be answered using mathematical optimisation models and Machine Learning. In recent years, Artificial Intelligence models have been developed in order to optimise the collection process (Wilson et al., 2021). Additionally, smart collection techniques emerged in recent years, utilising industry 4.0 technologies like IoT, big data, cloud technology, virtual technology, autonomous robots or Artificial Intelligence to make the collection process more resource efficient (Sun et al., 2022b).

Fuzzy Multi Criteria Decision Making Methods: A popular approach considering the collection of products, especially End-of-Life (EoL) products, is the utilisation of fuzzy logic and probabilistic models to make up for uncertainties regarding time, quantity, involved parties and more. The selection of locations for collection centres is thereby often optimised by multi criteria decision making (MCDM), which allows for the consideration of several, partially contradicting and complex criteria (Sagnak et al., 2021). MCDM methods like analytic network process (ANP), analytic hierarchy process (AHP), Best-Worst, DEMATEL or TOPSIS are combined with fuzzy set theory (FST) and fuzzy logic for improving the product disposition process (Ocampo et al., 2019; Sagnak et al., 2021).

Mixed-Integer Linear and Non-Linear Programming: Soleimani et al. (2017) investigate a multi-objective non-linear programming model for the green vehicle routing problem (GVRP) including pickup of EOL products using a fuzzy approach. Vahdani et al. (2012) present a possibilistic mixed non-linear programming model for facility location-allocation in closed loop supply chain network design, which shows efficiency improvements. Yang and Chen (2020) tackle the collection centre location problem using a multi-objective mixed integer linear programming and fuzzy ANP approach to improve the decision-making process.

Hierarchical Clustering: Another approach to solve the location allocation problem subject to transportation efficiency and cost of (collection) facilities is Hierarchical Clustering, an unsupervised Machine Learning technique, exploring the cluster patterns of data (Lin et al., 2021). Location allocation problems have also been solved by supervised Machine Learning techniques such as k-means clustering, applied to contexts other than collection centres (Zhou et al., 2020). Lin et al. (2021) provide a hierarchical clustering framework to optimise logistics processes by selecting facility nodes of logistics networks including warehouses, distribution centres and terminal stations, from a given set of options. Nanayakkara et al. (2022) develop a method optimising either the collection centre locations or which geographical areas are assigned to preexisting collection centres, using a three-step approach. First, ward-like hierarchical clustering with geographical constraints is applied, followed by the determination of the best location of initial collection centres (ICC), or selection of the best preexisting ICCs, for each cluster based on a centre of gravity calculation. From this point on, a network design is created and optimised regarding sustainability and other factors (Nanayakkara et al., 2022).

3.2.3 Warehousing Approaches Including AI Methods

Once the returned parts have been collected, the warehousing process begins as the next step in reverse logistics. This includes tasks such as inspection, sorting, consolidation and inventory management (Wilson et al., 2021). Typically, the condition of returned products is unknown and can vary widely. This makes inspection an essential and labour-intensive step in the warehousing process (Bai and Sarkis, 2013). The number of returns is also unknown, so the approaches described earlier in this study for predicting product returns play an important role in the planning of the warehousing process. This allows, for example, capacity to be planned and inventory management activities to be coordinated at an early stage (Wilson et al., 2021).

AI- and Vision-Based Systems: Sorting is an important step in the warehousing process as it is here that decisions are made on what to do with returned fashion products once they have arrived at the warehouse and been inspected. Based on the evaluation of the returned items, a decision can be made whether the garments should be reused, repaired, refurbished or recycled, all of which are steps in what is known as 'processing', which is described below. The aim of warehousing activities is to get returned items back into use as quickly as possible. To this end, the items are stored in consolidated form. Inventory activities such as counting, tracking, sorting are therefore common tasks in reverse logistics warehousing (Wilson et al., 2021). AI and vision-based systems can, for example, enable smart robots to recognise the different types of recyclable materials and sort them accordingly (Wang et al., 2020; Zhang et al., 2019).

Cobots and AI-Based Assistance Systems: Automated sorting often focuses on ensuring that workers do not come into contact with hazardous materials. For this reason, collaborative robots ('cobots') are increasingly being used, for example to complete a task started by a human worker (Sarc et al., 2019). But even in the context of the fashion and apparel supply chain, where hazardous components play a minor role in reverse logistics, it is important that decisions about reprocessing, reuse or recycling are made quickly in order to be as economical and environmentally as possible. To the best of our knowledge, there is no approach yet that offers an AI-based assistance system in the context of reverse logistics in the fashion and apparel sector to help organise the warehousing process.

3.2.4 Processing Approaches, Including AI Methods

The final step in reverse logistics is the processing of the returned goods depending on their condition. In a reverse logistics network as a part of a closed-loop supply chain, it is crucial to find an alternative to the destruction of garments or final disposal in landfills.

Decision Systems: In a circular economy model, subsequent to inspection and sorting, the goods are individually processed according to the best option available. Options usually include reuse, repair, remanufacturing, recycling or disposal (Wilson et al., 2021).

For that matter, Abdessalem et al. (2012) propose decision modeling to find the best reprocessing option for any EoL return and apply this technique in two industrial cases. Disassembly forms an essential part of the processing in reverse logistics and a candidate for AI applications (Wilson et al., 2021), but is rarely investigated for the fashion industry. Shahidzadeh and Shokouhyar (2022) performed a social media analysis, employing Convolutional Neural Networks (CNNs) and Long short-term memory (LSTM) to achieve consumer-centric disposition decision support for managers in RL (Shahidzadeh and Shokouhyar, 2022). For instance, extracted happiness spectra from tweets reveal the contentment of consumers with specific features, which is mapped onto one out of three decisions (refurbish, repair and reuse, recycling) (Shahidzadeh and Shokouhyar, 2022). From this approach, benchmarks for developing and developed countries are derived (Shahidzadeh and Shokouhyar, 2022). If in sufficiently good condition, goods such as garments can be directly resold in the primary market or in a secondary market. The most suitable market needs to be selected and the goods are integrated back into the forward supply chain. While there exist many recommender systems for apparel on the consumer side (Mohammed Abdulla et al., 2019; Kottage et al., 2018; Bellini et al., 2022), our literature review failed to find any AI- or non AI-based recommender system for finding the most suitable sales channel for returned items based on their properties.

Reusing, Remanufacturing and Recycling: When it comes to remanufacturing, using IoT technologies like RFID form one approach to improve the process. Kumar et al. (2015) propose an Chaos-based Interactive Artificial Bee Colony (CI-ABC) algorithm to test the effect of RFID in reverse logistics. The implementation of RFID leads to substantially increased overall costs due to the investments in equipment, however, the operational time performance increases more substantially. Fabric and apparel recycling strategies have been investigated in recent years (Xie et al., 2021). Lewis et al. (2017) propose a zero-waste model for second-hand apparel by finding repurposing strategies. Payne (2015) investigates open- and closed-loop recycling methods of textile products, also in the context of fashion. However, recycling techniques for textiles are still limited due to fragmentation of supply chains and limited technology, especially in the field of material separation (Sandvik and Stubbs, 2019). A new potential therefore lies in innovative materials as well as improved collection and enhanced collaboration among stakeholders (Sandvik and Stubbs, 2019). The first of the mentioned potentials has been tackled by Durham et al. (2015), who discuss important aspects to be considered in the design process, which can lead to improved recyclability at the end of the apparel life cycle. Furferi and Governi (2008) employ a matrix approach combined with a self-organising feature map (SOFM) and a feed-forward backpropagation artificial neural network (FFBP ANN)-based approach for colour classification of wool-clothing, also taking into account the respective recycling process and colour similarity to get an optimal colour and material when merging two wool-materials for recycling. In the scope of this paper, literature findings about recycling and remanufacturing of apparel are very limited, but relevant for future research.

All findings from the literature review above are summarised in Table 1.

4 AI-BASED RECOMMENDER SYSTEM

The identified research gaps in the area of data-driven and partially automated analysis of customer returns data are to be closed in the underlying research project, which is currently being conducted in Germany. Based on the findings of the state of the art, a conceptual approach for an AI-supported recommender system targeting the prediction of customer returns and the optimised handling of follow-up processes in the fashion and apparel industry was developed. Interviews and workshops with experts and stakeholders in the industry were conducted to ensure the application proximity and user-centric focus of the concept. The main components of the recommender system are explained in more detail below.

4.1 Prediction of Future Returns

The system component enables the user to view return probabilities at the item level. Machine Learning models are used to continuously predict the potential return based on product information, customer's previous orders, return history, shopping cart information combined with the payment method and the elapsed time since order as input variables. In addition, the reason for the return, such as quality related returns, bracketing or false item returns, will be determined. The system thus takes into account both customer-related and product-related return aspects. To train the Machine Learning models supervised, existing return data and completed orders from the systems are used, which include the ground truth variables of the return reason. Additionally, the Machine Learning results of all open orders will be aggregated and presented in a user-friendly dashboard. During the application of the system, the Machine Learning models are retrained cyclically based on the newly generated ground truth data. Thanks to the available and aggregated information, returns management processes can be triggered and planned earlier. Among other things, this leads to an acceleration of the processes while at the same time enabling targeted forecasts of future return costs.

4.2 Decision Assistance for a Sustainable Second Life Planning of Returns

Usually, returned items are assigned to appropriate follow-up processes based on the reason for return and an initial assessment. Possible processing steps include additional quality checks, repairs or cleaning. Finally, the goods are destroyed, recycled or sold as 'new' in a secondary channel. Decisions for the follow-up processes of returns have so far mostly been made manually and thus are prone to be subjectively influenced. In the second system component, all available information is used to recommend decisions on the follow-up process at a product level. With information about, for example, the duration of the return process, the reason for the return, the result of the first inspection, the product group and product type, an AI model is trained to issue a recommendation to the user on how to proceed with the returned goods and via which channel the item should be offered. The system is combined with developed metrics from sustainability analyses and expert information to additionally incorporate the sustainability influences resulting from the processes in the decision-making basis. By improving the quality of decisions and reducing process time, the system aims to optimise the process and reduce economic losses. Additionally, it aims to ensure that destruction or recycling of returned goods are only considered as the last option. This reduces the waste of material, the resulting carbon footprint and contributes to the circular economy in the fashion and apparel sector.

5 CONCLUSION AND FUTURE WORK

The fashion and apparel sector is responsible for the majority of returns in e-commerce. In the context of the present research, it could be shown that there are a large number of studies dealing with the topic of reverse logistics network design, but these studies mostly refer to the industrial sector, e.g. in the sense of remanufacturing. It is difficult to find research that deals specifically with the returns process of apparel products in the e-commerce sector. Some transfer of studies from other sectors is possible, but the large number of variants in the fashion and apparel sector and the sheer volume of returns pose a particular challenge for manufacturers and retailers. Due to the high environmental impact of the industry, additional research is needed, which should primarily deal with the most sustainable processing of returned articles and the optimisation potential for this in the context of reverse logistics processes. The paper provides an overview of relevant developments in the fashion and apparel industry and does not claim to be a systematic and complete review. However, given the environmental and economic relevance of the issue, this should also be the aim of further studies. Furthermore, it could be shown that although there are approaches to use AI and ML in the field of returns forecasting and reverse logistics network design, mathematical methods dominate and their suitability to the underlying complexity is limited due to the mostly static approaches. In addition, there are currently no appropriate AI and ML applications that can be integrated into a system that is used in practice (e.g. ERP or PDM). For these reasons, it is advisable to focus more on approaches and applications in the context of AI and ML in the future. The knowledge gained from this research will be used as a guideline for the design of an AI-based recommender system that will provide meaningful recommendations for the further processing of returns based on returns predictions, thus making a valuable contribution from an environmental and economic perspective in an industry that is responsible for heavy pollution.

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