A Structured Literature Review on the Application of Machine Learning in Retail

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Abstract: Machine learning (ML) has the potential to take on a variety of routine and non-routine tasks in brick-and-mortar and e-commerce. Many tasks previously executed manually are susceptible to computerization involving ML. Although procedure models for the introduction of ML across industries exist, it needs to be determined for which tasks in retail ML can be implemented. Hence, we conducted a structured literature review involving 225 research papers to derive possible ML application areas in retail along with the structure of a well-established information systems architecture. In total, we identified 20 application areas for ML in retail that mainly address decision-oriented and economic-operative tasks. We organized the application areas in a framework for practitioners and researchers to determine an appropriate ML usage in retail. Our analysis further revealed that while ML applications in offline retail focus on the article, in e-commerce the customer is pivotal for application areas of ML.

1 INTRODUCTION

It is estimated that by 2025 more than 150,000 mobile robots will be deployed in retail to execute routine work such as refilling shelves or preparing package dispatch making use of machine learning (ML) (Liang et al., 2019).However, ML cannot only be implemented to overtake cognitive routine tasks involving rule-based tasks (Goos et al., 2009), but can also spread into domains previously defined as non-routine tasks (e.g., handwriting recognition or car driving) (Veres et al., 2011). A recent study by Frey and Osborne (Frey and Osborne, 2017) identified that many tasks in online and offline retail are susceptible to computerization. Although retail in both offline and online environments involves a variety of tasks requiring different capabilities, a recent study by McKinsey revealed a high potential for automatizing in general and ML in retail (Manyika et al., 2017). The focus in retail is on primary and valuable tasks that are described by Schütte as economic-operative tasks (Schütte, 2017; Manyika et al., 2017)

Brick-and-mortar retailers have faced increasing competitive pressure in recent years, especially from online retailers. This process has been intensified in particular by the COVID-19 pandemic (Nicola et al., 2020). While the use of ML has become strongly established in e-commerce, the pressure on brick-and-mortar retailers is also increasing in this area (Große Holtforth, 2018). While brick-and-mortar retailers manage products, logistics, etc. on store level, online retailers focus on optimizations on the customer level (Schütte, 2017). E-commerce involves much data regarding its customers and unstructured data regarding their products (product reviews, products created by users on a marketplace) the situation in brick-and-mortar retail is different (D'Haen et al., 2012; Hütsch and Wulfert, 2021; Niu et al., 2017). The majority of data is present in a structured manner and data about articles is often self-managed by product owners. Additionally, there is only a limited amount of data about the customers potentially limiting the introduction of ML to only a few application areas.

The ML algorithm selection problem - also known as the combined algorithm selection and hyperparameter optimization (CASH) problem - poses a challenge to all ML practitioners (Thornton et al., 2013). This not only involves the selection of an algorithm that fits the data set and the economic problem of the retailer but also model selection and hyperparameter optimization (Biem, 2003). Due to the abundance of possible combinations of these factors and their influence on the quality of the result, it is essential to choose fitting factors (i.e. algorithm, model,

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and hyperparameter) that fit the underlying data as well as possible (Thornton et al., 2013). Recently, however, there have been created various automated ML tools for making these decisions, which greatly facilitate the real-world application of ML methods (Feurer et al., 2019). Thus, even practitioners who are non-experts in the various ML disciplines can achieve good results using automated ML tools and available procedure models for introducing ML. Although these tools exist, it is still necessary to have experts who determine which tasks can be supported or even automated by ML and who are able to create the increasingly complex ML models themselves (Hütsch and Wulfert, 2021). ML experts can be supported by industry-specific frameworks indicating possible ML applications. Such a framework can resemble an entry point for ML implementation in online and offline retail. However, existing literature reviews on the application of ML in retail are usually limited to one application area and focus only online or offline retail (Bousqaoui et al., 2018). Against this backdrop, we pose the following research question: *What tasks in (online and offline) retail can be supported by machine learning?* To address this research question, we provide an overview of multiple application areas for ML in retail. We conducted an application-centered literature review for extracting possible ML usages in retail (Vom Brocke et al., 2009). We make use of an agreed-upon reference model in retail to structure the identified ML application areas along with retail-specific tasks (Schütte, 2017). This paper is useful for the development of a customized strategy of ML in retail. Hence, we propose decision support for retailers the ML usage in specific application areas.

The remainder of this research paper is structured as follows: in section 2 we elaborate on fundamentals about retail information systems in general and ML in particular. Next, we elicit our structured literature review approach. While we present the identified application areas of ML in retail in section 4, we discuss ML's current and future applications in online and offline retail in section 5. This research closes with a brief conclusion and research outlook.

2 THEORETICAL BACKGROUND

Next, we discuss related litureture to retail information systems and machine learning.

2.1 Retail Information Systems

Since the ignition of the internet existing retailers either extended their traditional in-store business by an additional online channel or new companies were started up implementing an e-commerce business model and selling articles online without operating any brick-and-mortar stores (Rudolph et al., 2015). Regardless of the institutional-economic discussion of retail companies, the tasks intended with the trading functions are economically necessary (Laudon and Traver, 2020). These are the three basic functions bridging the discrepancy between manufacturer and customers in the streams in real goods (goods, services; returns), nominal goods (money, credits), and information across space, time, quantity, and quality (Barth et al., 2015). Facilitated by the ongoing digitalization of the retail sector, the three basic functions increasingly cope with digital product and price information, payment, logistics, and distribution processes (Levy et al., 2019). In e-commerce, trading transactions are carried out digitally to some degree (Laudon and Traver, 2020). The degree to which the transaction must be digital varies in the literature on a continuum between a completely digital transaction and only a small part of the procurement process (Laudon and Traver, 2020). Information systems in retail support the execution of the three trading functions and related tasks. They support the operational-dispositive, the business administration-administrative, and the controlling as well as corporate planning tasks (Becker and Schütte, 2004). They extend the components of merchandise management systems (merchandise planning, logistics, and settlement processes) by business intelligence and necessary corporate-administrative tasks in an integrative manner for carrying out the business processes of a retail company (Becker and Schütte, 2004; Schütte, 2017). The necessary tasks of a retailer and supporting information systems can be depicted in process models and reference models for the retail industry. Reference models comprise a high-level sketch of the system and application architecture of a specific company and part of its application architecture (Heinrich and Stelzer, 2009). In the current body of literature exists a number of reference models describing retail information systems (Becker and Schütte, 2004; Schütte, 2011; Aulkemeier et al., 2016b). In this article, we focus on the shell model as proposed by Schütte as it covers the whole value chain from manufacturer, wholesaler, and retailer to the end consumer, focuses on tasks on a business level, and is designed for both online and offline environments. The shell model is a task-oriented reference model for retail (Schütte, 2011). We use the task-oriented perspective to determine for which tasks ML is already applied in scientific literature. It follows the principle of separation of tasks and actors introduced by Ferstl and

Sinz (Ferstl and Sinz, 2013). The shell model copes with the identified shortcomings of the H-model such as the artificial separation between merchandise management and decision support systems. It consists of four separate but intertwined architectures for each of the aforementioned actors along a value chain. The retail architecture consists of five shells for the main retail tasks (master data, technical tasks, economic-operative tasks, administrative tasks, and decision-oriented tasks) of each actor and the retailer in particular (Schütte, 2017). Each shell consists of a series of tasks that form the components of the architecture. The tasks relevant for structuring the application areas are described in the analysis section (Section 4). The shell model is depicted in Figure 1.

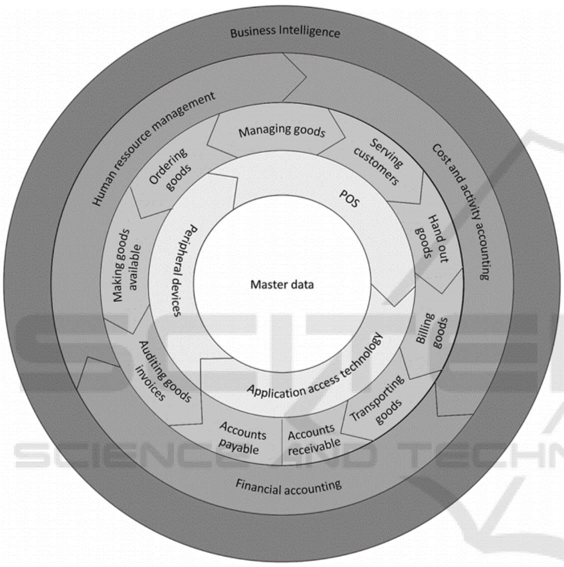


Figure 1: Retail information system architecture (Schütte, 2011; Schütte, 2017).

2.2 Machine Learning

Historically, computerization has largely been confined to manual and cognitive routine tasks involving explicit rule-based activities (Goos et al., 2009). Following recent technological advances, ML is now spreading to domains commonly defined as non-routine (Veres et al., 2011). As these non-routine tasks are commonly executed by human employees, this paper reviews research articles to investigate which of these non-routine tasks in offline and online retailing are support by ML in research and thus are potential candidates to support humans with ML in the future. We use the following definition of ML in which “a computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E” (Mitchell et al., 1997). To fulfill this definition an ML algorithm needs an optimization algorithm, an error function, a model and a data set. As we use some ML vocabulary in the remaining paper we clarify them in the following. A forecast is defined by historical time-series data that is used to make assumptions of possible events in the future. A classification algorithm makes statements about a data set and assigns this data to a given set of classes/ labels. There are a lot of other ML tasks which are mostly incorporated with a combination of forecasts and classification algorithms, which we mostly referred to as "*analysis*" in the following. In a similar work, Weber and Schütte (Weber and Schütte, 2019) inductively determined artificial intelligence use cases for brick-and-mortar retail from real-world examples. Although the broader term of artificial intelligence is used there, application areas of ML are also included. Just as in this paper, Weber and Schütte (Weber and Schütte, 2019) use the shell model as a starting point for the literature review (Figure 1). Both papers complement each other by identifying ML applications from practical contributions (Weber and Schütte, 2019) and from analyzing scientific contributions. The different approach of this paper makes sense, as the underlying research question is another one. In this paper potential application areas of ML in retail are reviewed by conducting research papers as a framework for practitioners and overview of researchers. Another related work by Bousqaoui et al. (Bousqaoui et al., 2018) focused on the use of ML in the domain of supply chain management.

3 SCIENTIFIC APPROACH

For identifying relevant application areas of ML in retail (online and offline), we followed the structured literature review approach as proposed by vom Brocke et al. (Vom Brocke et al., 2009). Following Cooper (Cooper, 1988) our literature review can be characterized as follows: We focus on research outcomes (use cases and ML algorithms for retail) and applications of ML in retail. We aim to integrate the body of literature and generalize application areas from available research. We neutrally represent articles from our exhaustive literature review with citations of selected papers for each application area. In this paper, we collect results from previous works and integrate them into an overarching framework. Our research addresses scholars specialized in the use of ML in retail and e-commerce and practitioners implementing ML algorithms.

We identify keywords from related literature and an initial literature screening resulting in a generic search query that consists of a retail and an ML part (Figure 2). As we derive existing application areas of ML in retail from relevant journals and conference papers and propose avenues for further ML application in this domain, we choose a broad literature scope. This broad scope is underpinned by the search engines SCOPUS, Web of Science (WoS), IEEE Xplore (IEEE), AIS electronic library (AISeL), and ACM, we query with their underlying databases that consist of research from, among others, economics and computer science literature. An initial query for title and keywords on 2021-04-15 resulted in an initial sample of 5,538 papers. To ensure an appropriate level of quality we focus on scientific literature and added additional quality criteria to the search (Randolph, 2009). We excluded non-English and non-German language articles; panels, and commentaries; purely technical articles (e.g., articles that focus exclusively on technological aspects without applying them in an e-commerce context); and articles with a pure e-commerce focus (e.g., articles that focus exclusively on e-commerce or sub-types without the inclusion of conceptual models). In contrast to previous research, such as Weber and Schütte (Weber and Schütte, 2019), we intentionally excluded white papers and practitioner reports. Based on the title and abstract considering the quality criteria, we reduce our sample to 410 papers. Further applying the approach of Bandara et al. (Bandara et al., 2015) to the content of the papers, we identified 261 relevant publications, leaving 197 after the exclusion of duplicates. We use a one-time for- and backward search to identify research that is presented as an alternative scenario resulting in 28 additional papers forming a final set of 225 papers (Figure 2).

Research areas and search string

Machine Learning	Retail
Mitchell et al. (1997), David and Dorn (2013), Goos et al. (2009)	Becker and Schütte (2004), Laudon and Traver (2020)
("Retail*" OR "Shop*" OR "*commerce" or "Sales*") AND ("Deep Learning" OR "Machine Learning")	

Literature screening and selection

Databases	ACM	AISeL	IEEE	Scopus	WoS
Initial Sample	84	79	224	4,902	249
Abstract Check	38	14	30	238	90
Content Check	11	9	22	156	60
Duplicate Check	197				
For-/Backward	28				
Final Sample	225				

Figure 2: Structured Literature Review Design.

The articles within the final set were independently analyzed by full-text screening and the relevant text passages including possible application areas were coded to refine the set of application areas. The shell model with its central master data objects (first shell), technical tasks (second shell), operational tasks (third shell), administrative tasks (fourth shell), and decision-oriented tasks (fifth shell) (Schütte, 2011) served as the basis for the coding, which was inductively adapted as needed. The initial set of possible application areas was refined using our final set of papers by two independent researchers in three coding rounds. After each round, the researchers met via online communication media to discuss the application area refinements. The framework in Figure 3 depicts the 20 application areas for ML in retail.

4 APPLICATION AREAS OF MACHINE LEARNING

In the following the application areas for ML are presented, which result from our structured literature review. The assignments between business tasks of the retail shell model and ML application area are visualized in figure 3. The number of identified scientific papers is visualized in brackets in Figure 3 for each application area. Each application area is assigned to a task of the shell model. We present each application area in general and the results of the literature review are described specifically by outlining a sample of the literature review results.

4.1 Decision-oriented Tasks

The decision-oriented tasks (i.e., business intelligence) of the shell model provide aggregated information to the management of a retailer (Schütte and Vetter, 2017). One very important business intelligence ML application area is the sales forecast, which is represented by 72 papers. The sales forecast provides management with information on future customer demands and therefore, management is able to plan operating activities accordingly.

Sales forecasting per article is one of the ML areas in retail that receives the most attention, because it is the basis for numerous advanced algorithms, such as price optimization (Chandrashekhara et al., 2019) or promotion optimization (Henzel and Sikora, 2020). Forecasting techniques are divided into four main groups: qualitative methods which are based on human judgment, time-series methods that use historical data, causal methods use rule-based forecasts, and simulation methods that simulate the behavior of the customer (Chopra et al., 2013). If the focus is on-demand forecasting with ML methods, time series methods are mostly used. The forecast for individual days has the difficulty that rare events are decisive in the prognosis, which are often hardly considered as outliers on weeks or monthly levels (Huber and Stuckenschmidt, 2020). The demand forecast can be extended by features, for example, Verstraete et al.

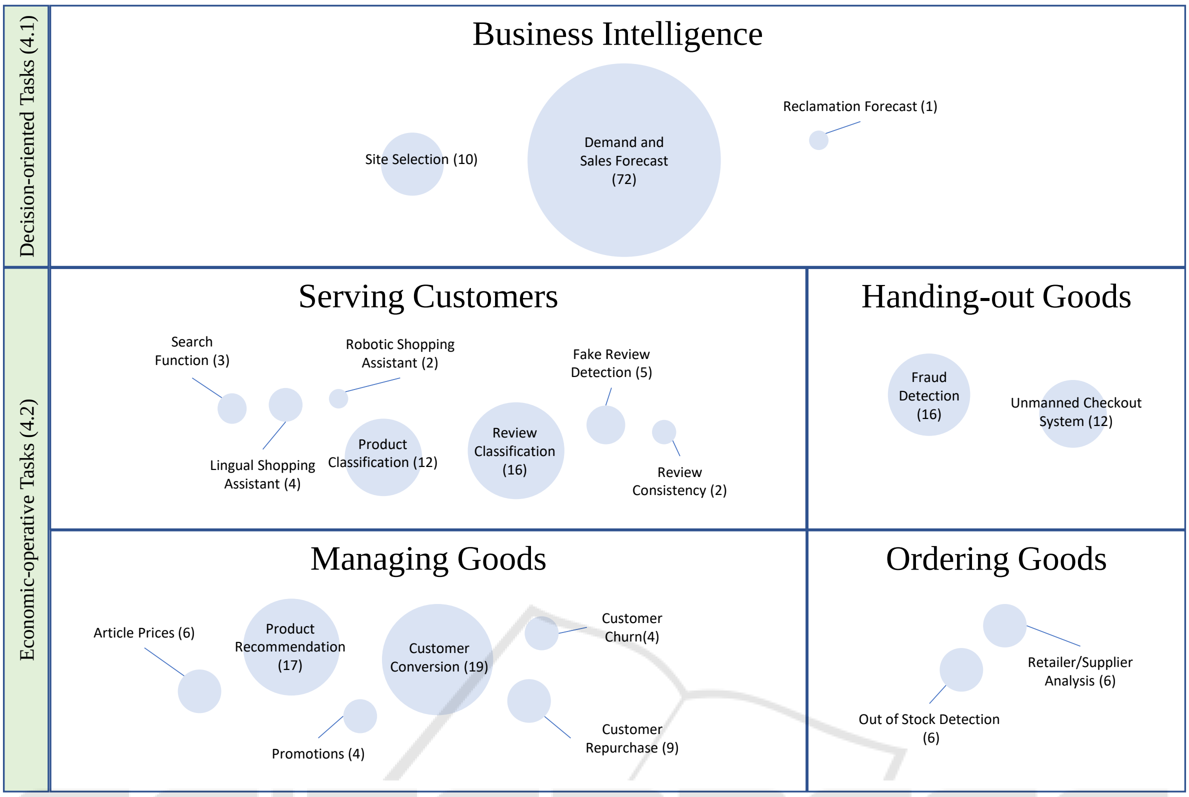


Figure 3: Framework for the Machine Learning Application in Retail.

(Verstraete et al., 2019) create a short-term and long-term forecast model that takes weather data into account. Loureiro et al.(Loureiro et al., 2018) compare demand forecasts in the context of the fashion industry, where short product life cycles take place.

The inverse of a sales forecast is the *forecast of returned goods*. For example, when it comes to product recalls, a high volume of returned products must be factored into operational activity planning by management. In addition, the returns process deals with goods that have been complained about. This can happen in case of wrong deliveries, faulty goods, or even defective goods (Becker and Schütte, 2004). Kumar et al. (Kumar et al., 2014) used multiple ML algorithms for the *reclamation forecast*. This forecast is integrated into supply chain design and planning problems to optimize supply chain tasks.

A store is an organizational unit that is used to document the goods in stock for inventory management and to map the associated business processes, such as goods receipt, physical inventory, and goods issue (Becker and Schütte, 2004). Part of the process for opening a new store includes the choice of location (*site selection*), which is done by management, where ML algorithms can support. For example, Wang et al.(Wang et al., 2018) make a quantitative site selection, so that a very large number of possible store locations are reduced to a small number, which is then investigated further by qualified employees. Machado et al.(Machado et al., 2015) follow a different approach in which a pre-selection has already been made and the remaining five stores are evaluated by a neural network. Another formulation of the site selection problem is when a mall is designed with a given set of sets. For example, Miao(Miao, 2020) uses ML algorithms to find a reasonable layout for shopping malls where the relationships of stores to each other are taken into account.

4.2 Economic-operative Tasks

The next subsections address the economic-operative tasks of the shell model, which are the primary activities of retailers. These tasks fulfill the bridging functions and resemble a retailer's value proposition (Levy et al., 2019). We have identified ML application areas for the tasks of managing goods, serving customers, hand out goods, and goods ordering.

4.2.1 Managing Goods

A central aspect of the economic-operative tasks is the managing of goods, which is reflected by a large number of papers (59) in this area. The task managing goods consists of the assortment policy, conditions policy (purchasing price and selling price), placement policy, and promotion policy. Prices are an important driver to influence how often an article is sold and the resulting profit margin. Therefore retailers can implement *price optimization* so that the demand fits the supply. For example, Chandrashekhara et al. (Chandrashekhara et al., 2019) determine the best prices of smartphones considering different features of the smartphones. Furthermore, *promotion optimization* can be used to specifically increase sales for a short period of time. The general promotional effect is forecasted by Henzel et al.(Henzel and Sikora, 2020) using. Retailers implement *product recommendation* systems to enhance the matching between supply- and demand-side participants, which we assign to promotional tasks and thus the task of the managing good. These systems recommend supply-side products to the customers based on previous purchases, ratings, or search behavior (Katarya and Verma, 2017). In contrast to the traditional recommendation that suggests popular products to customers, their algorithm aims at matching customers with appropriate niche products. Thus, online shops can more specifically target the long tail (McAfee and Brynjolfsson, 2017) and exploit niche markets to generate additional revue. For determining the ranking of products that should be recommended to demand-side participants, Liang et al. (Liang and Wang, 2019) perform sentiment analyses on analyzing online product reviews from Taobao.com. As personalized product recommendations may be biased by supply-side marketing endeavors, Wan et al. (Wan et al., 2020) propose ML algorithms to allow product recommendation in underrepresented market segments. The authors used two data sets from online shops selling apparel and electronics. Promotional efforts can be done for a special group of customers. To detect such a group of customers ML algorithms are used, which we also categorized to the promotional task.

An important application area of ML in retailing is *customer churner classification* (Li and Li, 2019). Clustering churners categorize demand-side participants into two clusters: one with churning customers and the other one with non-churning customers which results in a binary classification problem (Kim and Lee, 2012). While possible churners can be addressed with special marketing campaigns, the quality of services can be targeted at non-churning customers. Customer churn describes the loss of customers (Kim and Lee, 2012), which generated sales in the past and will no longer generate sales, mostly through an active decision to generate sales with a competitor. Keeping existing customers in the sales funnel is considered less expensive than acquiring new customers (Singh and Agrawal, 2019; Nikulin, 2016). Customer satisfaction has a positive influence on customer repurchase behavior(Jheng and Luo, 2019). To implement a *customer repurchase* analysis Kumar et al.(Kumar et al., 2019) used a combination of ML techniques by using customer characteristics and e-commerce attributes. This application area allows retailers to predict if a demand-side participant will rejoin the sales funnel resulting in additional sales transactions and revenue.

Using an ML algorithm on e-commerce data Singh et al.(Singh and Agrawal, 2019) suggest detecting very loyal customers and provide them with higher quality services to increase their satisfaction to retain them in the sales funnel. Jheng et al. (Jheng and Luo, 2019) mine transaction logs of an enterprise resource planning system at an online shop to predict customer repurchase behavior. Moreover, Mahaboob et al.(Mahaboob Basha et al., 2020) develop an ML model to describe the moderating role of customer loyalty on customer retention. Predicting the probability of a lead to convert into a customer and the profitability of this new customer is crucial in retailing (D'Haen et al., 2012). The *customer conversion* analysis implemented by D'Haen et al.(D'Haen et al., 2012) applies ML algorithm on sales data of a German B2B e-commerce company and complementary data crawled on the internet to predict the profitability of a lead. Knowing which leads will be profitable can support retailers by directly addressing these leads and increase their conversion probability. Niu et al.(Niu et al., 2017) apply multiple ML algorithms to predict the probability of a customer purchasing a product based on his (prior) search behavior. The computational model was applied to e-commerce data from Walmart. Thus, a retailer can predict the customer's willingness to purchase and pay in an early stage of a sales funnel (Blank and Dorf, 2012).

4.2.2 Serving Customers

The following application areas are concerned with tasks that serve customers. In brick-and-mortar stores, the products are made available through limited shelf space. The digital equivalent is the online stores, which often provide a much larger assortment. Therefore, a product *search function* is necessary to serve customers with their demand, which is the reason which we categorized the product search function to the business task. Khatwani et al.(Khatwani and Srivastava, 2016) develop a model for predicting customer's individual information search preferences using questionnaire data.

To enable a good product search, products must be classified first. E-commerce *product classification* is challenging due to the large scale and complexity of the product information and categories. Yu et al.(Yu et al., 2018) combine multiple ML algorithms to propose e-Commerce Text Classification. As reviews are the online counterpart to recommendations of an employee, we categorize review analysis with ML algorithms to the economic-operative tasks serving customers. To propel a retailer's role as a trustee they often implement systems to review the transaction partner and the products sold. Suppliers and customers of a retailer are aware of reviews as they often directly impact their business (Hussain et al., 2020). Vinodhini and Chandrasekaran (Vinodhini and Chandrasekaran, 2014) implemented based on the customers opinion (opinion mining) for *review classification*. They used publicly available customer reviews to classify the reviews into positive and negative reviews. So supply- and demand-side participants can preselect reviews possibly more relevant for them.

Opinion spammers and fake reviews exploit customer trust and harm the reputation of the retailer in e-commerce as a trustee by posting false or deceptive reviews (Zhang et al., 2016). These reviews are difficult to detect because of complex interactions between several user characteristics (Kumar et al., 2018). To enable *fake review detection* Hussain et al.(Hussain et al., 2020) implement a behavioral method that utilizes thirteen different behavioral features to calculate a review spam score for each reviewer. As review rankings are an important indicator for the relevance of the reviews to demand-side participants, the *review consistency* between review ranking and review summary is crucial. To verify this consistency Zhang et al.(Zhang et al., 2016) propose an ML approach based on e-commerce data. This approach enables demand-side participants to identify relevant reviews based on the review rankings. As reviews are often created by other customers, shopping assistance is more responsive to the need of a special customer and map the interaction with an employee digitally and automated.

Bertacchini et al.(Bertacchini et al., 2017) developed for a *robotic shopping assistant*. These measures serve to promote sales in general and can guide sales decisions. A shopping assistant can also be executed on a customer's smartphone as companion app (Wulfert et al., 2019). Many online shops offer a full 24-hour service implementing *lingual shopping assistants*. This service requires a lot of money when done manually. Chatbots can be used as a solution for automatic online shopping. Then the bot has to be able to give an accurate and quick answer. For example, Nursetyo et al.(Nursetyo et al., 2018) propose an intelligent chatbot system that can be used as an e-commerce assistant and therefore supports the process of serving customers.

4.2.3 Handing-out Goods

The business task hand out goods includes the transaction in which the product becomes the customer's property. This process can be improved or automated with ML algorithms. Kourouthanassis and Roussos(Kourouthanassis and Roussos, 2003) developed an *unmanned and automated checkout system* with a smart shopping cart. Shopping carts are unusual in the fashion industry segment, for example, Hauser et al.(Hauser et al., 2019) developed an ML algorithm to determine whether a product has passed the store exit or was only registered because it is placed near the gate-mounted antennas. Suponenkovs et al.(Suponenkovs et al., 2017) develop a system for *automatic invoice recognition* by analyzing the pixels with respect to their relevance and texture analysis. As an offline scenario, payment of fruits or vegetables in retail stores normally requires them to be manually identified. Rojas et al.(Rojas-Aranda et al., 2020) or Femling et al.(Femling et al., 2018) presents an image classification method with the goal of speeding up the checkout process in stores.

Since incorrect operation or failures by employees at the POS accounts for 24% of inventory differences in the retail industry (EHI, 2020), ML algorithms are used to reduce these differences. *Fraud detection* is assigned to the business task hand out goods, since problems with the transaction in which the product becomes the customer's property should be avoided. For interim transaction fraud detection at the checkout, Trinh et al.(Trinh et al., 2011) developed a method that uses image recognition to determine the hand movements of the cashier. It should be recognized by the algorithm whether all articles that are handed out to the customer are also recorded in a sales process, i.e. on the receipt. Fraud detection in retrospect must be dealt with in a human resources management process. Pehlivanli et al.(Pehlivanli et al., 2019) pursue a different approach by analyzing transaction data. ML algorithms are trained to classify fraud and non-fraud on the basis of indicators like profitability, stock turnover, stock cost, and shelf life. Furthermore, ML is used to classify the credit scores of customers in e-commerce. Kulkarni and Dhage(Kulkarni and Dhage, 2019) use ML and data mining techniques to integrate information crawled from social media to protect retailers from payment defaults.

4.2.4 Ordering Goods

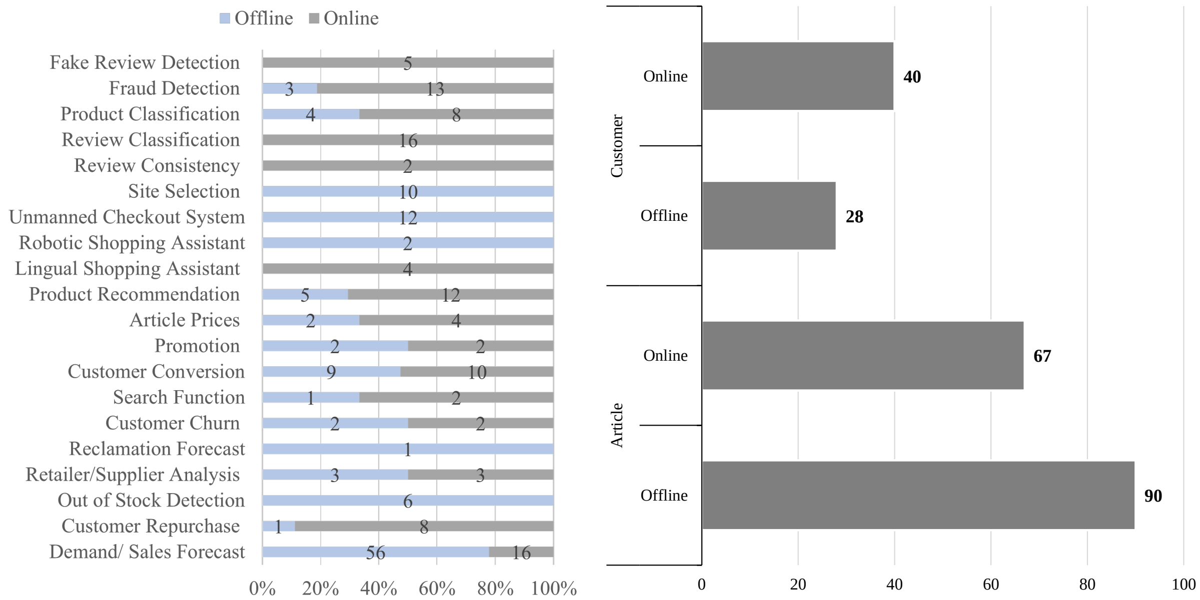
We identified out-of-stock-detection and supplier analysis as application areas of ML for the ordering goods tasks. Out-of-stock describes a shelf space in brick-and-mortar stores that are no longer filled by the intended article and is empty. Customer demands can no longer be fulfilled. As a *detected out-of-stock* triggers the replenishment process, this application area is assigned to the business task of making goods available. For example, Paolanti et al.(Paolanti et al., 2017) implement a mobile robot using visual and textual analysis to facilitate automatic detection of Shelf Out of Stock situations. Once the replenishment process is triggered, a supplier must be selected. Kuo et al.(Kuo et al., 2010) consider the aspect of sustainability of suppliers in their *supplier selection* optimization. ML algorithms are used to optimize the supplier selection problems regarding operational performance and environmental issues regarding the criteria corporate social responsibility, service, cost, environment, quality, and delivery.

5 DISCUSSION

Our structured literature review and the subsequent structuring of the ML application areas along the retail-related task depicted in the shell model (Figure 1) leads to the development of a framework for determining possible ML applications in retail (Figure 3). Our structured literature review on ML application areas in retail resulted in three major findings. First, a closer analysis of the framework reveals that there is a trend for supporting decision-oriented and economic-operative tasks in retail with ML. Other crucial tasks in retail such as master data management as well as technical and administrative task are either not covered by ML applications or underrepresented in our literature sample. On the one hand, the support and automation of economically valuable tasks seem reasonable as they resemble the main bridging functions, are the major value proposition, can be used to differentiate from competitors, and are a major source of revenue for retailers (Schütte, 2017). On the other hand, master data and technological facilities consist of the necessary data required for ML algorithms (Weber and Schütte, 2019). If this data is inconsistent or even not available, ML models provide false results or even cannot be trained. Second, our integrative approach for the review in brick-and-mortar retail and e-commerce is relatively balanced regarding the application environment with 107 papers from offline and 118 papers from online retail. It also reveals that ML applications make use of the peculiarities of each environment. While the selection of an optimal site for a brick-and-mortar store or the support of unmanned checkout systems with ML is an offline case, ML-based analyses of customers and product reviews are only possible in e-commerce scenarios in which these data exist (Hussain et al., 2020). As mentioned earlier, e-commerce involves much data regarding its customers and unstructured data regarding their products. This process is possibly further driven in future by VR (virtual reality) shopping. There, besides click and mouse movements in e-commerce, also hand, eye, head, or leg movements could be tracked (Xi and Hamari, 2019). We assume that existing application areas presented in this work, especially from e-commerce, can be adapted to VR shopping, and future research may find new application areas, especially for VR shopping (Xi and Hamari, 2019).

However, we also identified application areas that are applied in both environments such as customer conversion, promotion optimization, or product classification (Figure 4a). This trend is also supported by the fact that brick-and-mortar retailers are increasingly integrating technology within their stores to bring in online convenience and experience (Dekimpe et al., 2020).Product placement is a task necessary to optimize revenues in brick-and-mortar stores but can also be used in electronic shops to optimize the placement of a product on a website (Hütsch and Wulfert, 2021). As these ML models can be used in both environments, the effort for implementing can be balanced out by the dual application. Thus, these applications are useful for retails applying a multi- or omnichannel approach (Verhoef et al., 2015). Third, the analysis of the application areas for the object of interest reveals a tendency towards customer-centered application of ML in e-commerce (40 papers) while the focus in the offline environment is on a single or set of articles (90 papers) (Figure 4b). Our analysis also confirms the developments described by Grewal et al. (Grewal et al., 2017) towards a more customer-centered focus in brick-and-mortar retail (28 papers). However, we propose to focus even more on the customer for a proper ML implementation and address the customers' experience for value generation (Verhoef et al., 2009).For selecting the optimal site, it is necessary to identify a location with an adequate number of potential customers and select the right articles for the needs of a specific customer milieu (Wang et al., 2018).

Additionally, we concentrated on retail as the domain of application. Retail can be distinguished from wholesale by treating small units, trading net prices, and operating in a business-to-customer busi-



(a) Offline vs. Online ML Application Areas.

(b) Article- vs. Customer-centric ML Application Areas.

Figure 4: Application Area Analysis.

ness model (Levy et al., 2019). Although our framework for ML application is particularly developed for retail, we propose that many of the ML applications can also be used in a wholesale context as the tasks are similar on a broad level (i.e., bridging functions) comparing retail and wholesale architectures (Schütte, 2017). We intentionally focused our literature research on ML applications in scientific publications to ensure a maximum level of quality and comprehensibility of our research. However, we are aware that implementations in practice can be ahead of scientific publications (Eyes, 2021). Thus, we aim to integrate practitioner's sources such as company white papers and publications of retail interest groups in future research. We also opted for a broad research scope reflected in our search string and the databases queried. However, we did not provide a more detailed analysis of the algorithms and data used in each ML application with this broad scope. An important avenue for future research is to detail this overview and provide evidence for proper algorithms to be implemented within each application area. As we focused on identifying ML applications in retail, we used a task-oriented architecture by Schütte (Schütte, 2011) that focuses on the business layer as a starting point. However, we are aware that there exist other reference architectures covering additional application and technical architecture layers in general and integrating ML in particular (Aulkemeier et al., 2016b). Although these architectures include additional layers, they are less detailed with regard to retail-specific tasks. So it might be worthwhile for future research to extend existing task-oriented architectures (Schütte, 2017; Becker and Schütte, 2004) with technical layers integrating ML. Alternatively, an architecture may profit from providing interfaces to plug in additional services (e.g., ML services) making the architecture more flexible (Aulkemeier et al., 2016a).

6 CONCLUSION

We have identified 20 application areas of ML in offline and online retail based on a thorough analysis of the current body of literature. The application areas identified cover decision-oriented (business intelligence) and economic-operative tasks (managing goods, serving customers, handing out goods, ordering goods). Following our analysis, ML can be implemented to support and automatize structured and unstructured tasks in retail. Additionally, current research is equally concerned with the application of ML in offline and online retail. For e-commerce, we identified a tendency for a customer-centric usage of ML, while in the brick-and-mortar context the article is more often the object of interest. The contribution of our paper for practitioners and researchers is a general overview of current research on ML applications in retail. For practitioners, the framework of ML application can be applied by a retailer to check for which tasks ML can be implemented in the company. Thus, it can be used as an indicator for the usefulness of an ML application to check whether an ML implementation project is feasible and makes sense from an economic perspective. The algorithms developed and applied in the identified papers can also serve as a starting point for practical considerations for implementation. For researchers, this work provides a retail-specific framework for ML application in retail to foster the development of more holistic and integrated ML models (e.g., promotion-sensitive resource optimization).

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