Dynamization of Retail Pricing: From Traditional Price Determinants to Automation Based on Artificial Intelligence

Christian Daase[1][a], Seles Selvan[1], Dominic Strube[2][b], Daniel Staegemann[1][c], Jennifer Schietzel-Kalkbrenner[3][d] and Klaus Turowski[1][e]
[1]*Institute of Technical and Business Information Systems, Otto-von-Guericke University, Magdeburg, Germany*
[2]*Hochschule Wismar, University of Applied Sciences, Technology, Business and Design, Wismar, Germany*
[3]*Berufliche Hochschule Hamburg, Hamburg, Germany*

Keywords: Retail Pricing Model, Dynamic Pricing, Retail Revenue, Artificial Intelligence, Systematic Literature Review.

Abstract: Setting product prices poses both challenges and chances for retailers, as higher prices per stock keeping unit might lead to lower customer volume, while lower prices might result in insufficient turnover in relation to costs. In the age of digitalization and artificial intelligence, understanding price determinants becomes even more important as customer preferences shift and alternatives for purchasing products, such as online, are within easy reach. Based on a systematic literature review, this study aims to build a comprehensive model of traditional factors influencing customers' price perception as fair, with an extension towards AI-driven data integration and use case design to ultimately realize dynamic pricing models such as real-time demand pricing, personalized pricing and further machine learning-based approaches. The final visualization is intended as guidance for practitioners to evaluate their pricing strategies to determine if factors are currently being overlooked and to consider how they could be incorporated into future decisions. Researchers can also use the insights gained to build upon and expand the potential of AI integration into pricing automation.

1 INTRODUCTION

The retail sector is driving the global economy, and its significant economic impact underscores the importance of effective retail strategies. Although there are many definitions of retail, most have in common that the field encompasses activities surrounding the sale of items to consumers for personal use, including advertising, store management, and other services (Peterson and Balasubramanian 2002). While this definition corresponds to business models where products are sold directly to end consumers as the final link in the value creation chain, the emergence of new models such as direct-to-consumer (D2C) might necessitate a redefinition of parts of the current retail landscape (Daase et al. 2023).

Determining the final price of a product or service plays a crucial role in various retail types, which can generally be categorized into three main forms: brick-and-mortar (B&M) retailing (i.e., selling from a physical location), distance selling (i.e., including mail-order), and online retailing (Weber and Schütte 2019). Usually, estimating the *optimal* price, meaning the perfect balance between items sold, their associated production costs, and revenue earned (i.e., optimizing the price elasticity), is a difficult task for managers. The landscape has become more complex after the COVID-19 pandemic, significantly accelerating the transition to online shopping (Roggeveen and Sethuraman 2020).

Numerous successful or failed campaigns can be linked to immature pricing strategies. For example, the Indian automotive company Tata failed to position its model *Nano* on the market as the business

[a] https://orcid.org/0000-0003-4662-7055
[b] https://orcid.org/0000-0003-3017-5189
[c] https://orcid.org/0000-0001-9957-1003
[d] https://orcid.org/0009-0009-3782-4963
[e] https://orcid.org/0000-0002-4388-8914

Daase, C., Selvan, S., Strube, D., Staegemann, D., Schietzel-Kalkbrenner, J. and Turowski, K.
Dynamization of Retail Pricing: From Traditional Price Determinants to Automation Based on Artificial Intelligence.
DOI: 10.5220/0013441000003929

In *Proceedings of the 27th International Conference on Enterprise Information Systems (ICEIS 2025) - Volume 1*, pages 617-629
ISBN: 978-989-758-749-8; ISSN: 2184-4992

did not align the pricing with appropriate branding to ensure that customers perceive a realistic value, not just low costs. Although the Nano was marketed with good intentions as the world's cheapest vehicle, the branding led to it being perceived as poor quality and a poor man's car (Mukherjee 2021).

Although Walmart did not invent the concept of *everyday low pricing* (EDLP), its successful application was instrumental in its rapid ascent to the top of the Fortune 500 (Ellickson and Misra 2008). By consistently offering products at low prices without relying on frequent special offers or promotions, Walmart attracted a broad customer base and maintained a competitive edge. Despite the effectiveness of EDLP in establishing Walmart's dominance in the United States, the company struggled in the German market. This case illustrates regional variations in terms of successfully implementing a strategy in one region while the same approach fails in another (Ryu and Simpson 2011).

In addition to regional and cultural differences, pricing strategies must align with the target audience's financial situation and preferences. From a retailer's perspective, a thorough pricing strategy should take into account all relevant factors that influence pricing decisions, based on the company's aspirations on the one hand and the customers' requirements on the other. In recent decades, the retail landscape has shifted, in particular due to the advent of artificial intelligence (AI) and the rise of online shopping. Given the enormous amounts of customer data generated across various sectors like grocery, drugstores, and so on (Grewal et al. 2021), AI emerges as a potent tool capable of leveraging this data to guide retail decisions.

In the airline industry's distant past, buying a ticket months in advance usually guaranteed a lower price, while prices spiked as the departure date approached. However, this rigid, rule-based pricing often led to inefficiencies, such as insufficient capacity utilization due to high prices simply because the algorithm dictated it. As a result, airlines struggled to cover basic costs like fuel and potential customers were driven away by the lack of flexibility. In contrast, today's airlines have embraced dynamic pricing, a model that adjusts prices in real-time based on demand, availability, and other factors (Selçuk and Avşar 2019). This shift has allowed airlines to optimize revenue and better meet customer expectations. Incorporating AI-driven strategies can significantly enhance this process by providing more accurate demand forecasting, optimizing inventory levels, and dynamically adjusting pricing based on real-time data and market trends.

Given the complexity and range of issues retailers face today, a deeper understanding of the factors influencing effective pricing strategies becomes essential. In this paper, the following research question (RQ) is therefore addressed:

RQ: What are the determinant factors that should be considered in the development of traditional and AI-driven pricing approaches by retailers?

This paper aims to provide a comprehensive overview of the determinants for pricing decisions of retailers. Furthermore, a pricing model is compiled to illustrate the interdependence and possible categorization of the identified factors. In the final visualization, recent advances in automated data collection and AI enhancements are highlighted to complete the common thread towards modern data-driven pricing strategies in retail.

Following this introduction, Section 2 briefly describes the methodology of this study in terms of a systematic literature review (SLR). Section 3 examines determinants for defining an appropriate profit margin that the retailer can add to its own costs. Traditional and AI-driven pricing models with consideration of the retailer's costs are discussed in Section 4, before a unified model for price determination in the age of AI is presented in Section 5. The paper closes with a conclusion in Section 6.

2 METHODOLOGY

The basis of the research is derived by means of a systematic literature review (SLR), following the guidelines of vom Brocke et al. (2009) to enhance research robustness and scientific rigor. The SLR protocol is designed to identify relevant scholarly articles and case studies addressing traditional price determinants and AI-driven pricing strategies in retail. As primary databases, ScienceDirect and Emerald Insight were chosen for their extensive collections of peer-reviewed journals, reviews, and book chapters from the fields of business, economics, and information systems.

The search was further refined to the subject areas: business, management, and accounting, leading to the selected journals *Journal of Retailing*, *Journal of Retailing and Consumer Services*, *Journal of Business Research*, and *Industrial Marketing Management*. Furthermore, a forward and backward search was carried out throughout the SLR. Using the advanced search, the article titles were restricted to *retail*, *pricing* or *retail strategies*, and the abstracts were further specified to include *sales* or *purchases* in the period from 2005 to 2024. In Emerald Insight, the search was further narrowed to articles stating only *pricing* in titles and *retail* in abstracts.

The review was divided into three phases. First, the articles matching the given specifications were automatically retrieved. Second, the titles and abstracts of the articles were skimmed to assess their potential for further review. Third, the full texts were read and additional articles from the forward and backward searches were captured. Inclusion and exclusion criteria were applied throughout the review process as listed in Table 1.

Table 1: Selection criteria.

Inclusion	Exclusion
Written in English	Context other than retail
Published between 2005 and 2024	Introductions, sole abstracts, corrections
Focus on price determinants or factors to improve customer satisfaction	No peer review or outdated article
Possibility of AI automation for data retrieval or decision-making	Inappropriate methodology or superficial results

The review yielded a total of 61 articles from all journals, databases and forward and backward searches, as shown in Figure 1.

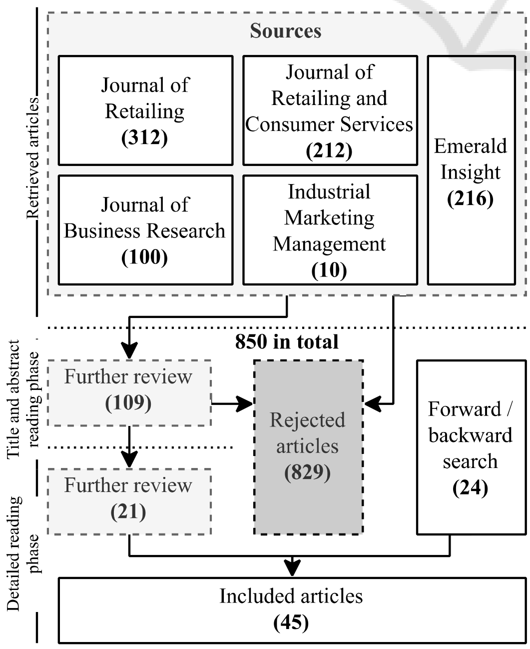

Figure 1: SLR search process.

3 DETERMINANTS OF PRICING

This section addresses the factors influencing the profit margin that a retailer can add to products. Although the cost to a retailer of procuring assortment items is the fundamental factor, it is outside the retailer's control unless the retailer is the manufacturer. Therefore, production costs are only briefly described in Section 4. The factors described in this section may also apply in part to manufacturers selling their products to intermediaries.

3.1 Market Factors

This section covers fundamental concepts and definitions of factors that can be directly influenced by the retail sector in general or by particular companies within it. This includes general marketing considerations, market structure and concentration, and retail channels and formats.

3.1.1 Marketing

In the business landscape, marketing functions as a bridge between firms and their target groups. Defining marketing can be challenging as the concept has continually evolved over the past decades and might be dynamically adjusted when a business grows. Bartels (1951) defines marketing as the "*field of study which investigates the conditions and laws affecting the distribution of commodities and services*". The definition describes marketing as a medium to exchange goods with consumers, thus being a mere channel for promoting products and services to the final target group.

However, the impact of today's marketers is far beyond this description. Historically viewed as transactional facilitators, marketers have emerged from an outdated view of themselves being solely sales representatives into planners of comprehensive value creation. The value creation process is complex due to shifting consumer behaviors and their growing knowledge of available products, especially with respect to modern digital means to search and compare products. Hence, R. Liu (2017) emphasizes the importance of developing methods to effectively identify, measure, and predict the ways in which marketing strategies would enhance perceived value during exchanges with customers.

Adapting to rapidly changing market conditions is vital for organizations' long-term success and growth. This goal can be achieved through marketing research and planning a suitable marketing strategy that appeals to customers and provides a competitive edge over rivals. A marketing strategy involves a series of decisions that allow a company to make crucial choices about its efforts and budget allocation in selected markets and segments (Varadarajan 2010). The marketing strategy process includes collecting and analyzing data concerning the market, customers, competitors, and industry trends to guide strategic decisions. It also involves segmenting the market into identifiable groups based on demographic, psychographic, geographic, or behavioral characteristics (Varadarajan 2010).

In summary, a sound marketing strategy can lead to an enhancement of perceived value to customers and an improved competitive public image. However, the cost of marketing must also be considered to decide whether it is worthwhile.

3.1.2 Market Structure

Market structure or concentration refers to measures that describe how the shares are distributed among participants in the market and how the competitive landscape looks like for the sector. The *Herfindahl-Hirschman index* (HHI) and *concentration ratios* (CR) are two exemplary indicators of market concentration (Naldi and Flamini 2014). HHI is considered to be a more precise measure because it takes into account all companies in an industry. The HHI is calculated as the sum of all squares of all market shares (i.e., *S*), thus leading to the following formula:

$$HHI = \sum_{i=1}^{n} S_i^2 \tag{1}$$

The HHI value offers insight into the degree of market concentration, where the maximum value (i.e., a value of 1) represents a monopoly and the minimum (i.e., 1 divided by the number of market participants) means perfectly balanced competition. From a mathematical perspective, markets can be considered non-concentrated if the index value is below 15 percent, moderately concentrated if the value is between 15 and 25 percent, and highly concentrated if the value exceeds 25 percent. Since in economics this type of formula usually employs whole numbers (e.g., 20 as percentage of market share instead of 0.2), the values could also be expressed as 1,500, 2,500, and so on (Pavic et al. 2016).

Before the emergence of the HHI, the CR index was a more common measure of concentration. While the HHI requires understanding the market shares of all companies participating, the CR can be applied to only the largest *n* companies (Naldi and Flamini 2014). The CR is determined by solely adding together the market shares of the enterprises, expressed as percentages, thus calculating how large the total market share of the biggest *n* companies is. Mathematically, it is denoted as the following formula:

$$CR_n = \sum_{i=1}^{n} S_i \tag{2}$$

The CR value can vary from almost 0 percent (for a highly scattered market) to 100 percent (if n is equal to the total number of market participants).

In terms of pricing, market power can have an impact on the extent to which a retailer can exploit its position, whether due to its unique regional proximity to customers or the originality of the items sold. However, the legal system needs to be factored in when the formation of monopolies or oligopolies is impending.

3.1.3 Retail Channels

Retail channels describe the various ways in which products can be distributed among customers. Different channels pose different challenges for retailers and also have an impact on reasonable pricing strategies as the costs to provide a certain channel differ from each other. The most widely provided channel is traditionally the physical retail branch. It offers direct customer interaction, creating a positive shopping experience and enables faster delivery, since the customers themselves need to visit the central location from which products are sold (Gauri et al. 2021).

Alternatively, products can also be sold via more than one channel. Beck and Rygl (2015) have created a taxonomy of different variations of co-existing retail channels. First, multi-channel retailing refers to the provision of multiple options for customers to purchase items (e.g., physical and online modes), while the channels may not be integrated with each other, meaning that no inventory or pricing data is shared between channels, nor do customers have the option to return items through a channel that was not used for the purchase. Secondly, cross-channel retailing refers to a model where multiple channels are integrated with each other so that customers can, for example, redeem a voucher in a physical store that has been sent to their mobile app. However, only the third model, known as omni-channel retailing, offers full integration of all channels at once.

Depending on the retail channels offered, price adjustments could be made taking into account the delivery speed and the improved shopping experience, for example if customers are willing to pay more when they have their purchases in their hands immediately. On the other hand, the channel provision costs need to be considered by the retailer.

3.1.4 Physical Retail Formats

Different retail formats have been established to meet the expectations of numerous groups of customers. Bonfrer et al. (2022) compiled a list of common stationary retail formats, including supermarkets, hypermarkets, discounters, mass merchandisers, convenience stores, and traditional stores. Supermarkets pose medium-sized to large spaces that are in physical proximity to their customers and sell everyday goods such as food. Hypermarkets are usually larger than supermarkets, sell additionally more general goods, and are designed to serve a higher number of customers, while being located in less urbanized areas. Discounters follow a rather low-price strategy by limiting the service level to a minimum and selling private label goods. Mass merchandisers may sell a wider range of general merchandise from different retail formats in an extensive manner like hypermarkets, but usually not focusing on food and everyday goods. Convenience stores usually belong to a retail chain and provide a small-sized assortment of essential items and food in highly urbanized areas. Lastly, traditional stores can be understood as independently owned small-sized shops. Changes in the structure of retail store formats across the global retail landscape have led retailers to reevaluate their roles within these formats (Bonfrer et al. 2022). Decisions regarding retail store formats are crucial as they determine attributes such as store size, location, layout, and customer service levels.

A retailer can either specialize in the assortment by selling items from a small spectrum and from only a few brands, or by diversifying the offered product categories. When adapting the pricing strategy, a retailer must therefore consider whether customers would prefer a specialized service over their desire to buy several products in one place. Possible costs here may be related to inventory management, rent, and personnel.

3.2 Retailers' Strategical Factors

This section covers factors related to a retailer's strategic direction based on its targeted role in the value chain. Furthermore, possible paths to improving the perceived value and shopping experience are addressed.

3.2.1 Strategic Impact of Pricing for Retailers

The worldwide economic decline from 2007 to early 2010 drove many companies to realign pricing strategies in order to keep certain sales levels and protect market share amidst reduced consumer spending and aggressive competitor price cuts, highlighting the strategic importance of pricing when used as a short-term tactical tool (Piercy et al. 2010).

In their study, Kienzler and Kowalkowski (2017) highlight that the primary issue identified in their analysis is the lack of comprehensive reviews that cover both business-to-consumer (B2C) and business-to-business (B2B) perspectives. Their research underscores that a well-crafted pricing strategy is vital for delivering customer value, guiding pricing decisions, and ensuring profitability. Crafting an effective pricing strategy is influenced not only by factors such as market conditions, company goals, and customer characteristics, but also the specific pricing context, which might also be part of the aforementioned strategic alignment.

Piercy et al. (2010) discuss various pricing strategies and their implications in competitive positioning and market dynamics. They analyze how companies use pricing approaches to navigate economic conditions and competition. The authors explore high-passive price strategies, where high prices are used to enhance margins and emphasizing non-price competitive factors, and low-active price strategies employed by discounters to attract price-sensitive customers through low prices, provided they maintain cost efficiency. Additionally, they address low-passive price strategies used by smaller firms with lower costs, where pricing is kept discreetly to avoid associating low prices with poor quality. These strategies highlight the complex interplay between pricing decisions and market positioning, as well as the importance of aligning pricing strategies with overall business objectives and market conditions.

While the pricing strategy details the company's method, the pricing objective specifies the particular goals the company seeks to accomplish through its pricing decisions. A sound pricing strategy for a retailer should align pricing with customer value perceptions, market conditions, and business objectives while effectively communicating value.

3.2.2 Reconsidering the Role of Retailers

The supply chain structure varies based on industry or type of merchandise. It typically involves moving goods from manufacturers to wholesalers to retailers or directly from manufacturers to retailers in a two-level supply chain. One such model is D2C retail, which refers to an approach where businesses interact with customers directly, without the involvement of intermediaries or platforms, bypassing traditional retail channels. Examples include brands like Warby Parker and Gymshark (Kim et al. 2021), which bypass traditional intermediaries and physical stores by selling directly to consumers, allowing these brands to achieve higher profit margins and offering high-quality products at more competitive prices.

Also, in certain scenarios, retailers do not sell directly to end consumers but function as intermediaries for businesses operating within a B2B model. In B2B retail or non-consumer retailing (Noad and Rogers 2008), retailers provide products to other businesses, which may use these products for further production, resale, or internal use. In this context, the retailer's role transitions from being the final point of sale to acting as a medium that facilitates the distribution of goods from manufacturers to other businesses. Therefore, they are not always the final entity in the supply chain, as their role can vary considerably based on the circumstances and strategic choices of the business.

The role a retailer takes in a supply chain affects how many profit margins are added to a product throughout its journey to the next owner. For the determination of the final price, this means that the minimum turnover must cover more margins in addition to the production costs the further away the retailer's position is from the manufacturer, or less margins the more the structure resembles a D2C model.

3.2.3 Store Formats

The design and purpose of a stationary store can have an impact on customers' perception of value and thus indirectly justify price adjustments. Depending on the product category, some attributes can only be perceived in person, such as tasting over a food sample (Rieländer 2023) or the comfort, fit and texture of clothing (Smink et al. 2019). While retailers may be tempted to exploit this unique feature of physical retail, it should be noted that one of the emerging challenges here may be showrooming (Wang and Wang 2022). This phenomenon describes the habit of consumers visiting physical stores to assess a product before searching online for a cheaper price. Retailers are therefore faced with the task of balancing the value-enhancing effects of their stores with the temptation of customers not to buy a product directly.

Another factor that can be considered in pricing is the customer's urge to purchase an item immediately, which is another feature of stationary retail compared to online shopping (Rieländer 2023). The design of a store can positively influence shopping behavior, whether by considering psychological factors such as the preferred walking direction of customers (Ferracuti et al. 2019) or by integrating in-store advertising (Han et al. 2022). In addition, physical retail is currently in a split situation where employees can no longer create as much added value for the customer as in the past, as consulting is increasingly being taken over by online reviews (Bellis and Johar 2020). However, personal contact and service is still valued, for example in the form of advice on food recipes (Rieländer 2023), but the level of value perception by customers for this needs to be kept high enough to cover the additional costs of staff through adjusted pricing of items.

3.3 Product Factors

A central aspect in pricing decisions is the product to be sold itself. Depending on the quality, use, and suitability for the current situation, different pricing models may be deemed as appropriate by customers. Furthermore, products can be advertised by their respective manufacturers in addition to the retailer's marketing efforts for their stores.

3.3.1 Product Life Cycle

Understanding the product life cycle (PLC), its exploitation, and possible extension can help retailers to align their pricing with the product's market position, which can influence its competitiveness in the retail landscape. An empirical study by Castelli and Brun (2010) emphasizes that the duration of the PLC is an important determinant of fashion retailers' pricing strategies. The study shows that demand in the maturity phase of products is usually predictable, allowing for high sales per stock keeping unit (SKU) and the ability to maintain full pricing over longer periods of time. Conversely, products that only reach the introduction and decline phases require more dynamic pricing strategies to adapt to rapidly changing market trends.

The *console war* between the Nintendo 64 and Sony's PlayStation serves as a classic example of strategic pricing in an oligopolistic competitive market, illustrating how different pricing strategies align with the PLC. The analysis by H. Liu (2010) highlights Sony's use of price skimming and penetration pricing to gain a competitive edge.

Initially, Sony focused on price skimming by setting a high price for the PlayStation to appeal to extreme gamers to maximize revenue from early adopters. As the product transitioned to the growth stage, Sony lowered the price to attract casual gamers, using penetration pricing to expand its market share. These pricing tactics not only optimized revenue and market positioning but also demonstrated the critical role of understanding the market structure and consumer segmentation in pricing decisions.

3.3.2 Seasonality

Weather can affect the appeal of certain products, such as snow shovels during winter storms or sunscreen on sunny days. Retail firms traditionally manage demand uncertainty through strategies such as adjusting product assortments, quick responses, and end-of-season price markdowns. However, weather can unexpectedly influence sales, with events like early cold snaps in winter or early warming in spring affecting inventory turnover and pricing (Bertrand et al. 2015). In the apparel industry, these seasonal changes are further complicated by the need to continuously introduce new fashion collections throughout the year to draw consumers back to stores (Bertrand et al. 2015). Thus, integrating weather considerations into inventory and pricing strategies is crucial for effectively managing demand uncertainty and optimizing sales performance.

Other researchers highlight how weather can affect consumer spending. For example, sunshine might boost the mood by lowering negative emotions, leading to increased spending (Murray et al. 2010). Badorf and Hoberg (2020) conducted an analysis of data from the German stores, revealing that weather influences sales in complex, non-linear ways, with variations across different seasons, store locations, and product categories. For example, weather can cause sales in individual stores to fluctuate by up to 23 percent on the same day, and its impact on different product categories can vary significantly. In addition, short-term weather forecasts can increase the accuracy of the sales forecast by up to 1.5 percent, while their effectiveness decreases with longer forecast periods. However, since the study is limited to the German market, insights might differ under other circumstances.

3.3.3 Product Branding

If neither physical distance nor the assortment in terms of product categories are distinguishable factors for different pricing approaches, the quality of service and the subjective perception of certain product brands could become decisive. Service quality has emerged as a critical element influencing consumer decisions (Lu et al. 2011). This includes various aspects, such as providing effective post-sale support, engaging in impactful advertising, and ensuring timely and efficient repairs. These service components not only help in differentiating a brand but also play a crucial role in building and maintaining customer loyalty. Successful companies like IBM and HP use their strong service reputations to secure a competitive advantage (Lu et al. 2011), which in turn can help the retailers who sell their products.

Advertising fulfills two main roles: institutional advertising, which seeks to enhance brand awareness for the retail store, and promotional advertising, which aims to boost traffic and sales for particular products (Kumar et al. 2017). Interdependencies between factors such as brand loyalty and PLC stage might have an impact on the effectiveness of advertising, with new brands benefiting more from the advertising measures than already well-established ones (Kumar et al. 2017). Effective branding also enables a company to differentiate itself in a competitive market by creating a distinctive identity. As discussed in the introductory chapter, the example of the Tata Nano (Mukherjee 2021) illustrates how inappropriate branding can lead to an unintended association of the product with negative attributes.

Premium brands can usually be sold at higher prices than comparable products, but the profit margin for the retailer depends on the retailer's own cost of procuring the goods. Brand advertising, in addition to the marketing efforts of the retailer, can increase customer awareness of an offer and thus positively influence the urge to buy a particular product in a specific store.

3.4 Consumer Factors

As a final category, the potential customers themselves with their general overarching characteristics, which are summarized under the term socio-demographics, or with their very specific preferences can be used by retailers as decision support for their pricing strategies.

3.4.1 Socio-Demographics

Consumer factors such as purchasing power, preferences, and price sensitivity can significantly impact pricing decisions. Socio-demographics refers to the study and analysis of a population or group's statistical characteristics. These include factors such as age, gender, income, education, household size, social status, and so on (Weech-Maldonado et al. 2017).

For example, Simonovska (2015) found that the prices of identical apparel products sold by Mango, a Spanish apparel manufacturer, are positively correlated with the per-capita income of the destination country, indicating price discrimination based on consumer income. The price elasticity estimates suggest that generally higher-income countries have lower price sensitivity, leading to higher prices for identical items in those markets.

The work by Ellickson and Misra (2008) also highlights the significance of consumer socio-demographics in shaping pricing strategies. It is assumed that retailers tend to select pricing strategies based on the preferences of their target audience. Their findings suggest that lower-income consumers tend to favor *everyday low pricing*, while higher-income consumers tend to favor *high-low pricing models* (i.e., regular promotions). Gauri et al. (2008) also observed that as the average income and population density in the market area rise, retailers show a preference for a high-low or hybrid pricing strategy.

3.4.2 Consumer Preferences

Besides socio-demographic factors, the personal preferences of consumers can also influence purchasing decisions and, conversely, the optimal pricing strategy of a retailer, even if they are partly dependent on overarching economic circumstances.

The study by Binkley and Chen (2016) emphasizes the impact of customers' preferences for prices and store formats, with geographic proximity being a significant factor. They discovered that shoppers who buy many items in one trip tend to pay higher prices on average, likely due to not searching for the best deals. Furthermore, convenience appears to be the primary factor in store choice, with those living closer to supercenters and conventional supermarkets paying higher average prices.

Key factors influencing customers' preferences can also be related to the store's atmosphere, including location and convenience, with car owners favoring stores that offer good parking facilities (Maslakçi et al. 2021). An inviting store atmosphere, exceptional service, and a prime location can boost customer spending and encourage continuing noticeable shopping behavior in the future. Consumer preferences can also be influenced by gender. In a study conducted by Mortimer and Clarke (2011), it was found that men place less importance on store ambiance compared to women. Female shoppers prioritize weekly specials, regular discounts, and promotional pricing more than men. However, men placed slightly more importance on the availability of the specific items they are looking for.

In summary, preferences for store formats and geographic proximity shape purchasing decisions. Convenience and the appeal of the store atmosphere are crucial to consumers' motivation and shopping habits, and therefore their willingness to pay certain prices.

4 PRICING MODELS

This section provides an overview of traditional and rather static pricing models and a comparison with more recent, dynamic AI- driven approaches.

4.1 Traditional Pricing Models

Once the retailer has determined the costs of a product, the price can be set using various pricing strategies, which can be extended by the previously established determinants, provided these are known. Examples of common traditional pricing strategies, without claiming to be exhaustive, are *cost-plus pricing*, *value-based pricing*, *everyday low pricing*, *high-low pricing*, and *competitive pricing*.

Cost-plus pricing describes the sole approach of first calculating the costs that the retailer has for procuring the assortment items and then adding a desired profit margin. If costs increase, it is generally considered fair for the retailer to increase the retail price, while it is considered unfair if prices are increased due to market share and power (Alnes and Haugom 2024). However, the originally targeted profit margin can be influenced by the market position at the time. Value-based pricing, on the other hand, incorporates the perceived value to the customer into the pricing decision. This can include the frequency, volume, and duration of use in a quantity-based approach or the availability of a product or solution at a certain time/price ratio in an outcome-based approach (Sharma and Iyer 2011).

Everyday-low-pricing, as introduced earlier, is a strategy that demands retailers to offer low prices regularly on products without the need for frequent promotions (Ellickson and Misra 2008). In contrast, high-low pricing is a strategy where a retailer maintains a high regular price for a product and occasionally offers substantial discounts (Fassnacht and El Husseini 2013). In competitive markets, retailers may also take into account the pricing decisions of other participants, possibly including the strategic factors described in Section 3.2 (Sharma and Iyer 2011), leading to the competitive pricing model.

4.2 AI-Driven Pricing Models

While traditional strategies provide stability, AI-driven pricing offers predictability and adaptability. Among established or tested dynamic pricing strategies implemented with the help of AI are *real-time demand pricing*, *personalized pricing*, and generic forms of *machine learning-based pricing*.

The aim of dynamic pricing is to adjust prices for goods in real-time in response to factors such as demand, supply, competition. Vomberg (2021) describes dynamic pricing in two key dimensions, frequency and range of price changes. The former specifies the number of price changes within a certain timeframe (i.e., how often prices are adjusted), while the latter refers to the intensity of changes in that timeframe (i.e., the difference between the highest and the lowest price). Real-time demand pricing focuses on reacting instantaneous to changes in demand. By leveraging real-time data and analytics, this strategy dynamically sets prices according to the demand for a product or service. This strategy is particularly recognizable in goods markets where demand changes very frequently, such as electricity (Fang and Wang 2023) or gasoline (Perdiguero García 2010). Pricing, in which prices are tailored to individual customer characteristics, behaviors, and preferences can be termed as personalized pricing. Individualizing prices is achieved by using the information consumers leave behind as digital traces (Vomberg 2021).

Machine learning (ML) models continuously refine and improve the price determination process based on historical data, customer interactions, market dynamics, and any data that can be provided as a suitable feature set. In addition to processing historical sales data, ML models can uncover unseen patterns in the data that humans might not have noticed (Subbarayudu et al. 2023).

4.2.1 Shift Towards AI – Data Perspective

From a data perspective, AI-driven pricing involves the utilization of large datasets to fine-tune pricing strategies. This approach allows businesses to react to market fluctuations quickly, understand customer needs, and implement pricing strategies that are both responsive and backed by data.

In the traditional approach, retailers often relied on simplistic pricing models and educated guesses, which could lead to inefficiencies such as overstocking and reduced sales from poorly informed decisions. Weber and Schütte (2019) discuss the application of ML in various areas of the retail industry. Techniques such as classification, predictive analytics, clustering, optimization, and ranking algorithms, rely heavily on data to function effectively. By categorizing products, forecasting sales, segmenting customers, and optimizing operations, these methods demonstrate how vital data is in making informed decisions and enhancing efficiency in retail.

Kayikci et al. (2022) introduce a four-stage data-driven dynamic pricing strategy intended to reduce food waste in Turkish retailers, utilizing hyperspectral imaging sensors to evaluate the freshness of produce. Starting from a *freshness stage*, where the product's initial price is set, the price decreases until the food reaches the final *disposal stage* in case it was not sold. This model aims to optimize pricing throughout the freshness lifecycle of the product, thereby minimizing food waste and improving profitability.

A lot of the data mentioned can be difficult to handle or even to collect in manual decision-making processes. However, by using AI technologies, data can be collected from sensors, smart devices, social networks, and cameras, for example, and further processed with numerical or image and video analytics (Daase et al. 2023; Haertel et al. 2022).

4.2.2 Shift Towards AI – Solution Perspective

AI-driven pricing strategies extend beyond merely setting prices but can also adopt a solution-centric approach that enhances customer satisfaction. Grewal et al. (2023) explore the transformative impact of digital innovations on the retail industry by examining in-store technologies' effects on customers and employees. For example, employees' efficiency might be boosted through security robots for crime prevention, cleaning robots, or robots that scan shelves for missing items. Examples of technologies that can improve the customer experience include self-checkout and payment systems, personalized discounts, and information about the environmental impact of a product (Grewal et al. 2023).

With in-store video analytics, some retailers are focusing on fine-tuning their stores for optimization. An experiment by Ferracuti et al. (2019) identified popular store departments and shopper routes using *real-time location systems* that allow to develop targeted marketing and merchandising strategies based on consumer behavior. In this way, retailers can enhance store profitability by concentrating marketing efforts on high-traffic areas where shoppers spend more time. In terms of pricing strategies, it is conceivable that the correct placement of items could entice customers to buy them, even if they were not originally intending to do so, rather than relying on an unusually low price to tempt customers to visit the area of the store with that item.

AI integration can help in two ways, either by increasing the reasonable price of a product or by reducing a retailer's overall costs, which would be distributed proportionally across the SKUs sold. Price increases can be justified by an improved customer experience while cost reductions can be achieved through theft prevention or automation, for example.

5 PRICING STRATEGY MODEL

The model of factors influencing the pricing strategy derived from the SLR is illustrated in Figure 2. Starting from the production cost of a product and the manufacturer's profit margin (if the supply chain does not follow the D2C scheme), the retailer's profit margin is added. General market factors include, as described in Section 3.1, marketing efforts, the current market structure, the retail channels that can be offered in the given environment and, if provided by the retailer, the physical retail formats. In terms of interconnections, marketing can be used as a tool to increase market share and thus the power to set the pivotal prices for goods. If a physical assortment is maintained, there may be a trade-off between specialization (i.e. customers value the specialized service and distinguished item selection) and diversification (i.e. customers value the ability to buy different products in one trip). Since pure online stores can have distributed storage capacities and customers do not have to spend a lot of effort to switch from one rather specialized online store to another, this category is more prevalent in stationary retail. Costs associated with the pricing of products are a significant part of this category. Marketing costs, channel provision costs, inventory and facility management must be taken into account in the overall revenue calculation, as well as legal considerations if required by current market power and local regulations.

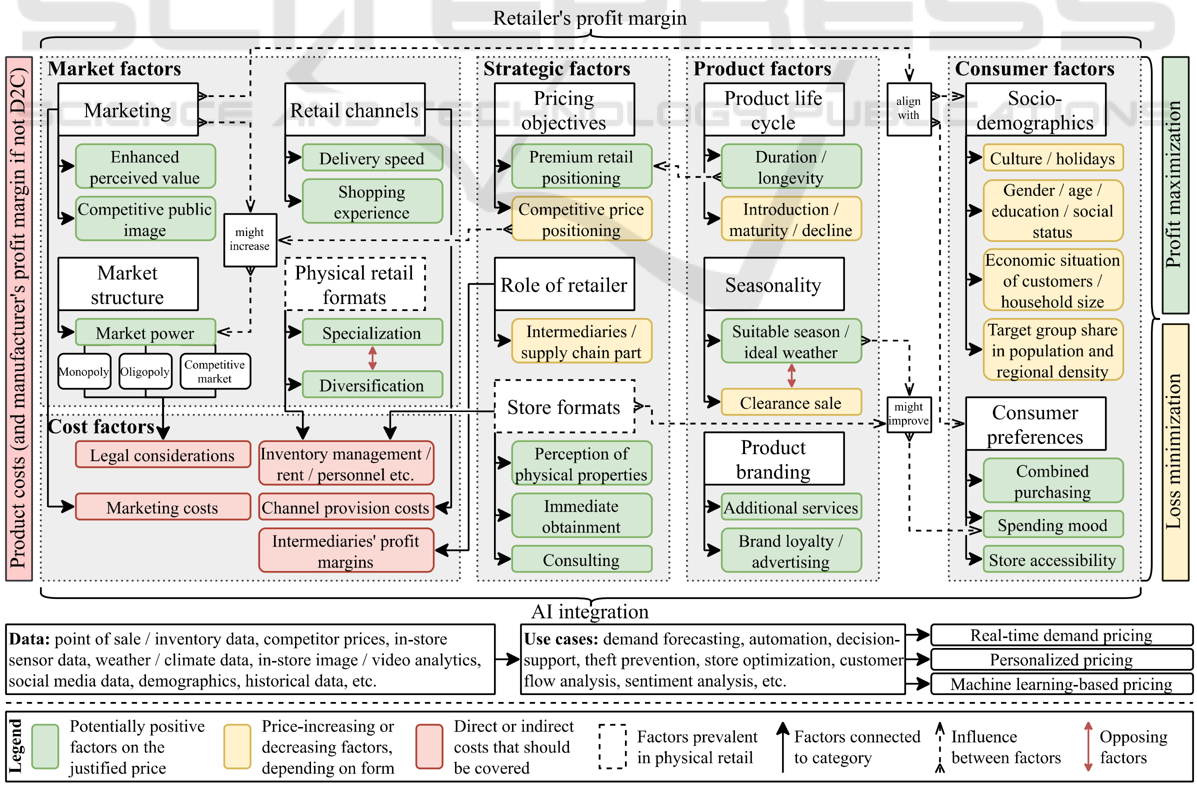

Figure 2: Price determination model and potential for AI integration.

Strategic factors, as described in Section 3.2, include the underlying objectives of the pricing strategy chosen by the retailer, the desired role within the supply chain and the store formats in terms of the external perception that customers should receive. Here, competitive price positioning can have a positive impact on market power in the long term by paying for it with the short-term disadvantages of lower prices. Similarly, the role of the retailer in the supply chain can have ambiguous effects. The further away the retailer is from the manufacturer, the greater the profit margins that have already been added to the cost of production and that must be factored into the final price. However, the role of the retailer as the final point of sale offers a wider range of usable influencing factors, as shown in the figure.

The third category (product factors), as described in Section 3.3, summarizes the effects based on the PLC, seasonality and specific product branding. Similar to the competitive price positioning from the previous category, taking into account the current stage of acceptance of a product in the market can either help to consolidate its position or exploit the achieved need of customers to own it. The PLC, and in particular all factors related to the quality of a product, can further enhance the retailer's strategic direction as a seller of premium goods. In terms of seasonality, ideal climatic conditions (e.g., due to the time of year) can further enhance the utility value of a product. However, as the season comes to an end and this incentive diminishes, retailers may want to implement clearance sales to avoid potential losses while reducing their profit margin.

Lastly, the consumer factors described in Section 3.4 can be considered the most contextual ones. Socio-demographics such as culture, statistical distributions and the average economic situation can either positively or negatively influence the prices that can be charged for certain goods at different times of the year. Consumer preferences, on the other hand, are more tangible for retailers as they can be extracted from historical data or market research. While both categories form the basis for marketing efforts to target consumers, spending mood, as a vague concept, can be improved in different ways, for example through the store atmosphere or generally good weather. All of the retailer's efforts in setting product prices ultimately lead either to profit maximization or to loss minimization if the cost categories shown in the figure cannot be fully compensated.

AI integration, as outlined in Section 4.2, consists of three parts: data sourcing, use case solutions and the implementation of an appropriate pricing strategy. Useful data can be manifold, including information from physical retail such as video data, sales and inventory data, and digital sources such as social media. In addition, statistical information in conjunction with demographics or aggregated historical and competitor data can play a central role. Similarly diverse are the individual use cases that can be fueled by this data, ranging from customer behavior and sentiment analysis to cost-reducing use cases such as theft prevention, store optimization and automation. More generally, demand forecasting and decision support for managers pave the way for real-time demand pricing, personalized pricing and other generic ML-based pricing strategies.

6 CONCLUSION

This paper builds on research related to retail pricing and marketing and aims to provide clarity on the determinants of pricing decisions. In addition, modern AI-driven data collection and use cases related to price factor categories and corresponding dynamic pricing strategies such as real-time demand pricing, personalized pricing, and general ML-based pricing approaches are presented.

From a theoretical perspective, this paper extends beyond the exploration of individual price determinants and their exact mathematical relationships by presenting an abstract pricing model in Figure 2 including all factors identified in the literature that should be considered by retailers. From a practical perspective, participants in real markets can use the model to review their pricing strategies to determine if there are factors that have been overlooked and to consider how currently neglected factors might be incorporated into future pricing decisions. As the SLR is not exhaustive, future research could extend the findings by including more sources and refining the model. As AI is a field that is currently in constant evolution, the technical implications may also need to be adapted.

REFERENCES

Alnes, P. K., & Haugom, E. (2024). The effects of price framing and magnitude of price differences on perceived fairness when switching from static to variable pricing. In *Journal of Retailing and Consumer Services*, *81*, 103952.

Badorf, F., & Hoberg, K. (2020). The impact of daily weather on retail sales: An empirical study in brick-and-mortar stores. In *Journal of Retailing and Consumer Services*, *52*, 101921.

Bartels, R. (1951). Can Marketing be a Science? In *Journal of Marketing*, *15*(3), 319–328.

Beck, N., & Rygl, D. (2015). Categorization of multiple channel retailing in Multi-, Cross-, and Omni‐Channel Retailing for retailers and retailing. In *Journal of Retailing and Consumer Services*, *27*, 170–178.

Bellis, E. de, & Johar, G. V. (2020). Autonomous Shopping Systems: Identifying and Overcoming Barriers to Consumer Adoption. In *Journal of Retailing*, *96*(1), 74–87.

Bertrand, J.-L., Brusset, X., & Fortin, M. (2015). Assessing and hedging the cost of unseasonal weather: Case of the apparel sector. In *European Journal of Operational Research*, *244*(1), 261–276.

Binkley, J. K., & Chen, S. E. (2016). Consumer Shopping Strategies and Prices Paid in Retail Food Markets. In *Journal of Consumer Affairs*, *50*(3), 557–584.

Bonfrer, A., Chintagunta, P., & Dhar, S. (2022). Retail store formats, competition and shopper behavior: A Systematic review. In *Journal of Retailing*, *98*(1), 71–91.

Castelli, C. M., & Brun, A. (2010). Alignment of retail channels in the fashion supply chain. In *International Journal of Retail & Distribution Management*, *38*(1), 24–44.

Daase, C., Volk, M., Staegemann, D., & Turowski, K. (2023). The Future of Commerce: Linking Modern Retailing Characteristics with Cloud Computing Capabilities. In *Proceedings of the 25th International Conference on Enterprise Information Systems*. SCITEPRESS - Science and Technology Publications.

Ellickson, P. B., & Misra, S. (2008). Supermarket Pricing Strategies. In *Marketing Science*, *27*(5), 811–828.

Fang, D., & Wang, P. (2023). Optimal real-time pricing and electricity package by retail electric providers based on social learning. In *Energy Economics*, *117*, 106442.

Fassnacht, M., & El Husseini, S. (2013). EDLP versus Hi–Lo pricing strategies in retailing—a state of the art article. In *Journal of Business Economics*, *83*(3), 259–289.

Ferracuti, N., Norscini, C., Frontoni, E., Gabellini, P., Paolanti, M., & Placidi, V. (2019). A business application of RTLS technology in Intelligent Retail Environment: Defining the shopper's preferred path and its segmentation. In *Journal of Retailing and Consumer Services*, *47*, 184–194.

Gauri, D. K [Dinesh Kumar], Jindal, R. P., Ratchford, B., Fox, E., Bhatnagar, A., Pandey, A., Navallo, J. R., Fogarty, J., Carr, S., & Howerton, E. (2021). Evolution of retail formats: Past, present, and future. In *Journal of Retailing*, *97*(1), 42–61.

Gauri, D. K [Dinesh Kumar], Trivedi, M., & Grewal, D. (2008). Understanding the Determinants of Retail Strategy: An Empirical Analysis. In *Journal of Retailing*, *84*(3), 256–267.

Grewal, D., Benoit, S., Noble, S. M., Guha, A., Ahlbom, C.-P., & Nordfält, J. (2023). Leveraging In-Store Technology and AI: Increasing Customer and Employee Efficiency and Enhancing their Experiences. In *Journal of Retailing*, *99*(4), 487–504.

Grewal, D., Gauri, D. K [Dinesh K.], Roggeveen, A. L., & Sethuraman, R. (2021). Strategizing Retailing in the New Technology Era. In *Journal of Retailing*, *97*(1), 6–12.

Haertel, C., Nahhas, A., Daase, C., Volk, M., & and Turowski, K. (2022). A Holistic View of Adaptive Supply Chain in Retailing Industry. In *AMCIS 2022 Proceedings*.

Han, Y., Chandukala, S. R., & Li, S. (2022). Impact of different types of in-store displays on consumer purchase behavior. In *Journal of Retailing*, *98*(3), 432–452.

Kayikci, Y., Demir, S., Mangla, S. K., Subramanian, N., & Koc, B. (2022). Data-driven optimal dynamic pricing strategy for reducing perishable food waste at retailers. In *Journal of Cleaner Production*, *344*, 131068.

Kienzler, M., & Kowalkowski, C. (2017). Pricing strategy: A review of 22 years of marketing research. In *Journal of Business Research*, *78*, 101–110.

Kim, N. L., Shin, D. C., & Kim, G. (2021). Determinants of consumer attitudes and re-purchase intentions toward direct-to-consumer (DTC) brands. In *Fashion and Textiles*, *8*(1).

Kumar, V., Anand, A., & Song, H. (2017). Future of Retailer Profitability: An Organizing Framework. In *Journal of Retailing*, *93*(1), 96–119.

Liu, H. (2010). Dynamics of Pricing in the Video Game Console Market: Skimming or Penetration? In *Journal of Marketing Research*, *47*(3), 428–443.

Liu, R. (2017). A Reappraisal on Marketing Definition and Marketing Theory. In *Journal of Eastern European and Central Asian Research*, *4*(2).

Lu, J.-C., Tsao, Y.-C., & Charoensiriwath, C. (2011). Competition under manufacturer service and retail price. In *Economic Modelling*, *28*(3), 1256–1264.

Maslakçi, A., Yeşilada, F., & Yeşilada, T. (2021). The Moderating Role of Shopping Frequency on the Relationship Between Store Image and Satisfaction: Evidence from Cyprus. In *International Journal of Business*, *26*(2), 1–16.

Mortimer, G., & Clarke, P. (2011). Supermarket consumers and gender differences relating to their perceived importance levels of store characteristics. In *Journal of Retailing and Consumer Services*, *18*(6), 575–585.

Mukherjee, J. (2021). Tata Nano: Case of Repositioning: Case Analysis. In *Vikalpa: The Journal for Decision Makers*, *46*(3), 188–190.

Murray, K. B., Di Muro, F., Finn, A., & Popkowski Leszczyc, P. (2010). The effect of weather on consumer spending. In *Journal of Retailing and Consumer Services*, *17*(6), 512–520.

Naldi, M., & Flamini, M. (2014). The CR4 Index and the Interval Estimation of the Herfindahl-Hirschman Index: An Empirical Comparison. In *SSRN Electronic Journal*.

Noad, J., & Rogers, B. (2008). The importance of retail atmospherics in B2B retailing: the case of BOC. In *International Journal of Retail & Distribution Management*, *36*(12), 1002–1014.

Pavic, I., Galetic, F., & Piplica, D. (2016). Similarities and Differences between the CR and HHI as an Indicator of Market Concentration and Market Power. In *British Journal of Economics, Management & Trade*, *13*(1), 1–8.

Perdiguero García, J. (2010). Dynamic pricing in the spanish gasoline market: A tacit collusion equilibrium. In *Energy Policy*, *38*(4), 1931–1937.

Peterson, R. A., & Balasubramanian, S. (2002). Retailing in the 21st century: reflections and prologue to research. In *Journal of Retailing*, *78*(1), 9–16.

Piercy, N. F., Cravens, D. W., & Lane, N. (2010). Thinking strategically about pricing decisions. In *Journal of Business Strategy*, *31*(5), 38–48.

Rieländer, P. (2023). Creating Value Through Value Creation: How the Stationary Grocery Trade Creates Added Value for Its Customers in Times of Online Competition. In *Multisensory in Stationary Retail*. Springer Fachmedien Wiesbaden.

Roggeveen, A. L., & Sethuraman, R. (2020). How the COVID-19 Pandemic May Change the World of Retailing. In *Journal of Retailing*, *96*(2), 169–171.

Ryu, J. S., & Simpson, J. J. (2011). Retail internationalization: Lessons from "Big Three" global retailers' failure cases. In *Journal of Business and Retail Management Research*, *6*(1).

Selçuk, A. M., & Avșar, Z. M. (2019). Dynamic pricing in airline revenue management. In *Journal of Mathematical Analysis and Applications*, *478*(2), 1191–1217.

Sharma, A., & Iyer, G. R. (2011). Are pricing policies an impediment to the success of customer solutions? In *Industrial Marketing Management*, *40*(5), 723–729.

Simonovska, I. (2015). Income Differences and Prices of Tradables: Insights from an Online Retailer. In *The Review of Economic Studies*, *82*(4), 1612–1656.

Smink, A. R., Frowijn, S., van Reijmersdal, E. A., van Noort, G., & Neijens, P. C. (2019). Try online before you buy: How does shopping with augmented reality affect brand responses and personal data disclosure. In *Electronic Commerce Research and Applications*, *35*, 100854.

Subbarayudu, Y., Reddy, G. V., Raj, M. V. K., Uday, K., Fasiuddin, M. D., & Vishal, P. (2023). An efficient novel approach to E-commerce retail price optimization through machine learning. In *E3S Web of Conferences*, *391*, 1104.

Varadarajan, R. (2010). Strategic marketing and marketing strategy: domain, definition, fundamental issues and foundational premises. In *Journal of the Academy of Marketing Science*, *38*(2), 119–140.

vom Brocke, J., Simons, A., Niehaves, B., Riemer, K., Plattfaut, R., & Cleven, A. (2009). Reconstructing the Giant: On the Importance of Rigour in Documenting the Literature Search Process. In In *ECIS 2009 Proceedings*.

Vomberg, A. (2021). Pricing in the digital age: A roadmap to becoming a dynamic pricing retailer. In *The digital transformation handbook ‐ From academic research to practical insights*. University of Groningen Press.

Wang, J., & Wang, S. (2022). Revisiting the showrooming effect on online and offline retailers: The strategic role of in-store service. In *Journal of Retailing and Consumer Services*, *66*, 102884.

Weber, F., & Schütte, R. (2019). A Domain-Oriented Analysis of the Impact of Machine Learning—The Case of Retailing. In *Big Data and Cognitive Computing*, *3*(1), 11.

Weech-Maldonado, R., Miller, M. J., & Lord, J. C. (2017). The Relationships Among Socio-Demographics, Perceived Health, and Happiness. In *Applied Research in Quality of Life*, *12*(2), 289–302.