Acta Universitatis Danubius
ŒCONOMICA

# Algorithm Pricing and Algorithm Biases in Retail: A Systematic Review

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**Abstract**: **Objectives:** This review aims to analyse existing literature on the various algorithmic pricing strategies used in retail environments. It focuses on how these algorithms can unintentionally reinforce biases and discusses effective ways to avoid or manage such biases in retail. **Prior Work:** As retailers adopt more advanced algorithms, the risk of unintentional and often discriminatory biases becomes an important concern. **Approach:** A systematic review of literature was conducted using the PRISMA protocol, with data sourced from the Scopus and Web of Science databases. **Results:** Literature documents dynamic and personalised pricing as major forms of algorithmic pricing in retail, where prices are differentiated according to customer behaviour, market and customer data. Algorithm biases stem from input data biases, model design biases, and contextual and application biases. **Value:** The study recommends careful examination of input data, transparency, explainability and human oversight to manage algorithmic biases in retail effectively.

**Keywords:** algorithm pricing; algorithm biases; discrimination; ethical practices

**JEL Classification:** O32

## 1. Introduction

The adoption of artificial intelligence (AI) in retail is increasing, with machine learning algorithms used to improve customer experiences by offering customised

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services through chatbots, virtual assistants and product recommendations. Post the COVID-19 pandemic, online selling is on the rise locally, regionally, and globally, with retail giants like Amazon, Temu, Alibaba, Walmart and Shein among the leading retailers in the global markets selling beyond geographical borders. Local retailers in developed and developing nations have also adopted online selling and deliver products right to the doorsteps of clients, reducing costs for both the client and the company using smart shelves (Anica-Popa et al., 2021). The future of work in retail predicts the automation of most routine tasks that do not involve critical thinking, hence the increasing automation of major retailing activities like marketing, inventory management, price optimisation and customer management.

Behind AI-enhanced retail services are large amounts of consumer data collected to train and support AI, machine learning and deep learning algorithms. Machine learning is a process where machines learn from data and enhance their performance over time through various techniques such as unsupervised, supervised, semi-supervised and reinforcement learning. When a model learns from data, it identifies patterns and utilises them to make predictions or informed decisions. In retail, algorithms are developed and used for different purposes such as searching, recommendation, allocation, surveillance or monitoring, pricing, communication, filtering data, prediction and scoring (OECD, 2023). Pricing algorithm systems are trained to set prices in real time using personalised, market and customer data. The use of algorithm pricing has proved to be more profitable and vital, as retailers who set prices using algorithm pricing perform better than retailers who use traditional pricing methods (Hufnagel, Schwaiger & Weritz, 2022).

There remains an unending debate on the level of trust and control that management should allow for AI systems. Pricing algorithms can exhibit discriminatory and unfair pricing, which can cause harm to vulnerable populations, as prices of some basic products affect the welfare of consumers. Consumers do not seem to benefit and have different perceptions of differentiated prices. Vuyyuru (2025) noted an increasing loss of trust by consumers because of algorithm bias, especially where discriminatory pricing or data privacy issues are experienced, making consumers dissatisfied and less likely to associate themselves with the retailer. There is a literature gap concerning a comprehensive review of algorithm pricing and bias in retail. Algorithm bias in retail services has far-reaching implications for customer service, logistics, and company profit. Kittipanya-ngam, Tan and Cavite (2025) argued for the ethical and sustainable adoption of AI, where AI systems are developed and used in ways that support long-term environmental, economic, and social well-being while respecting core ethical principles and values. This review addresses the following research questions:

1. How is algorithmic pricing in retail conceptualised in the literature?
2. What sources and manifestations of algorithmic bias have been documented in

retail?

3. How best can algorithm biases be managed?

## 2. Research Methodology

The purpose of conducting this systematic literature review was to critically assess the existing body of knowledge on algorithm pricing and biases, delineate its boundaries and identify potential research gaps. The systematic literature review adopted the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol and adhered to best practices of conducting literature reviews implemented by Tetteh et al. (2024). The review was conducted in three major phases: planning. conducting, and documenting.

### 2.1. Planning

In the planning phase, the research question and the purpose of the systematic literature review were established (Tetteh et al., 2024). Previous literature was assessed to determine the keywords used for searching articles and the databases. Different keyword search strings were employed in the data collection process to extract more articles (Akter et al., 2022). In the Web of Science database, the search string ((algorithmic pricing OR dynamic pricing OR automated pricing OR pricing algorithms OR AI pricing) AND (algorithmic bias OR pricing bias OR discrimination OR fairness OR transparency) AND (retail OR online retail OR e-commerce OR brick-and-mortar OR supermarkets)) was used, whilst in the Scopus database the search string (algorithmic pricing OR dynamic pricing OR automated pricing OR pricing algorithms OR AI pricing) was used.

### 2.2. Conducting

In the conducting phase, relevant papers were identified, screened and exported from search databases (Tetteh et al., 2024). The initial search in Web of Science yielded 209 documents, whilst the initial search in Scopus yielded 146 documents; however, after screening for context and relevance, only 73 articles were selected for research inclusion. The inclusion criteria included only articles written in English, published articles, conference papers, books, and book chapters. Only papers published in the last 10 years were considered for inclusion.

### 2.3. Documenting

After identifying the relevant primary articles, the author and one reviewer conducted an in-depth analysis to mitigate potential validity threats arising from researcher bias. Studies were analysed, and themes were deduced from the literature itself, guided by the research questions of the study. Themes were categorised and coded. To ensure consistency and quality, the author conducted a comprehensive review of each activity, consolidating the research findings and synthesising an evidence-based systematic literature review. Figure 1 illustrates the screening process and the articles selected for analysis.

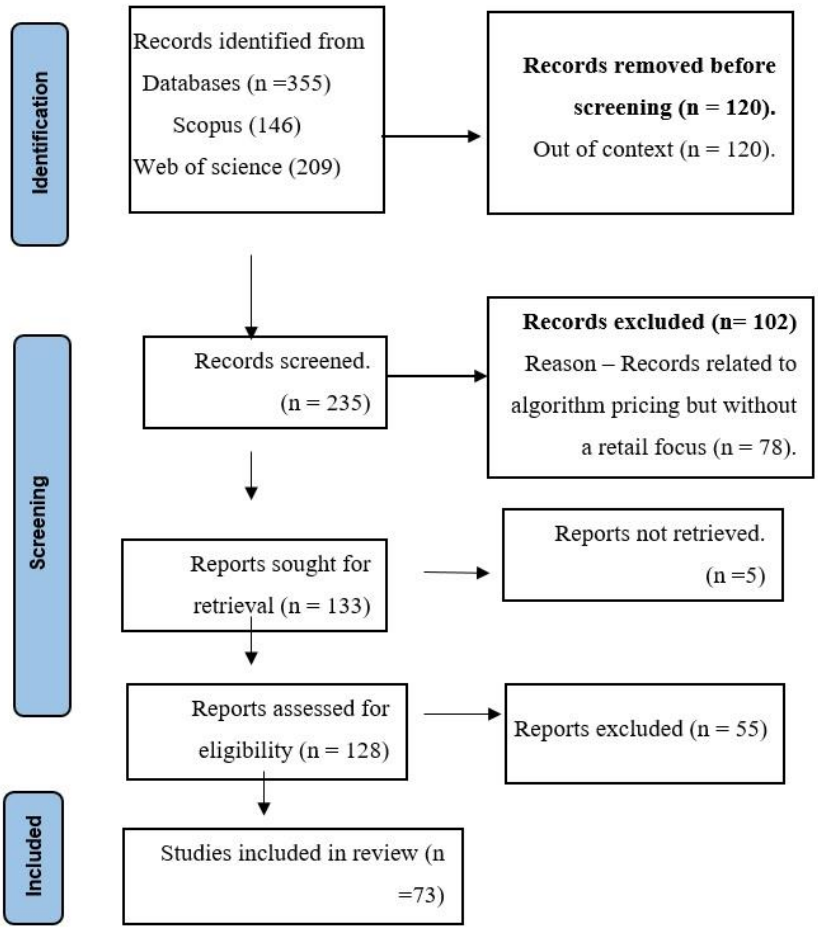



**Figure 1. PRISMA flow chart of the literature review process**

*Source: Author compilation (2026)*

## 3. Results

### 3.1. Algorithm Pricing Conceptualisation

Algorithm pricing, or algorithmic pricing, is the pricing of goods and services using artificial intelligence systems or the use of programs to automate the setting of prices (Spann et al., 2025). The literature documents two major forms of algorithm pricing, namely dynamic pricing and personalised pricing. This section conceptualises these forms of algorithm pricing.

#### 3.1.1. Dynamic Pricing

In dynamic pricing, embedded algorithms determine flexible prices according to market and customer data, helping firms increase revenue (Ho et al., 2026). The pricing strategy is defined by five core interlinked characteristics, namely dynamic value orientation, data quality, digitalisation of pricing, algorithmic-driven decision-making and reduction in the cost of changing prices (Nunan & Domenico, 2022). That is, the pricing strategy facilitates rapid and accurate matching of pricing to value, which cannot be achieved easily through traditional pricing strategies; utilises the vast and growing volume of training data available on which to make pricing decisions; shifts away from managerially based pricing to algorithm-driven decision-making in pricing and ultimately reduces the cost of setting prices (Nunan & Domenico, 2022). The literature explains the application of dynamic pricing in five major ways, as explained below.

**Theme one: Time-based pricing**

Algorithms set prices according to time, taking into consideration that some hours of the day experience higher demand compared to other hours of the day. Hence, to manage demand, service providers can increase prices of a particular product during peak hours where demand is exceptionally high and lower prices during other hours where demand is generally low or normal. Full-time-based prices of a particular product can change intraday or multiple times within very few hours (Tang et al., 2021; Aparicio & Misra, 2023).

Time-based pricing assists brick-and-mortar grocery stores to smooth demand during peak hours by differentiating the peak-hour and normal-hour prices; however, this pricing method offers no benefit to consumers, as it affects their welfare when prices of essential products suddenly increase during the day, yet increasing consumer anxiety (Tang et al., 2021). Literature documents a wide adoption of this pricing strategy across various industries, including grocery shops, transport, and restaurants.

**Theme two: Location or market pricing**

Algorithms also differentiate prices according to locations or different segments of

the market. Location reflects different socio-demographic characteristics like cultural patterns, income status, lifestyle, and economic activity. Algorithms are trained to differentiate prices according to these characteristics. This pricing strategy is widely adopted by both online retailers and offline brick-and-mortar retailers. However, locational pricing can cause harmful discrimination against certain groups of the community (Aparicio et al., 2023).

**Theme three: Algorithm Competitor price monitoring and matching**

Competitor price monitoring refers to the collection, processing, and transmission of retail price data and other marketing and promotional strategies. Algorithms are trained to monitor the prices set by other suppliers, competitors or third-party sellers, then leverage such information by pricing down on popular items to outcompete rivals and expand market share, or, on the contrary, by pricing up to take advantage of a rise in demand or competitors' low inventory (Shapiro, 2024). Price monitoring, matching or agreements between competitors in price margins can facilitate price collusion, which is capable of continuous price increases which are not based on demand and supply forces but on algorithms competing against each other. Hence causing harm to consumers (Nunan & Domenico, 2022; Shapiro, 2024).

The literature, however, documents high disparities in prices from different service providers, reflecting the capability of algorithms in differentiating prices of separate service providers. However, cases of price matching where algorithms match the prices of competing retailers were noted. Hence, this causes algorithm competition, which can be morally harmful if all the pricing algorithms are not monitored. That is, a pricing algorithm that is trained to charge a price of 5% lower than a major competitor can continuously increase prices whenever the competitor increases its pricing, causing pricing collusion and algorithm pricing competition (Aparicio et al., 2023).

**Theme four: Randomised promotional pricing**

The price of a service or a product is an important factor considered by consumers when buying; hence retailers use randomised pricing to promote certain products at particular periods, for example towards the expiry of perishable goods or towards the end of the season of a product. The temporary lowering of prices, which can be for less than a day or a few hours, attracts more consumers (Wu & Zhao, 2023).

### 3.1.2. Personalised Pricing

Personalised pricing is the practice of price discriminating consumers based on their personal characteristics and conduct, resulting in each consumer being charged a price that is a function of, but not necessarily equal to, willingness to pay. Unlike dynamic pricing, which bases its pricing decisions on market and customer data, personalised pricing mainly focuses on customer characteristics, willingness to pay

and customer behaviour. There is no consensus on the benefits of personalised pricing in the literature. Whilst some authors mention the benefit of increasing revenue by tailoring charges to customers and value creation by providing personalised prices, other authors argue that personalised differentiated pricing results in negative emotional experiences for price-disadvantaged consumers and affects customers' distributive fairness perceptions, which influence customer buying behaviour (Wamsler et al., 2022; Hufnagel et al., 2022). Perceived unfairness of prices by customers results in lower trust, a decrease in the likelihood to purchase from the retailer, spread of negative word of mouth, legal risks and consumer criticism and increased engagement in comparison search activities (Hufnagel et al., 2022). Dubus (2024) argues that personalised prices are more effective when charged to high-value consumers compared to low-value customers.

### 3.2. Sources of Algorithm Biases

An algorithm is a formally specified sequence of logical operations that provides step-by-step instructions for computers to process data and automate decisions (Moussawi et al., 2024). Algorithm biases refer to a deviation from standards that can be attributed to algorithm design, socio-cultural contexts or marketing applications (Akter et al., 2022). Additionally, when the outputs of an algorithm benefit or disadvantage certain individuals or groups more than others without a justified reason for such unequal impacts, the algorithm is biased (Kordzadeh & Ghasemaghaei, 2022). Algorithm biases originate from operational inequalities and quality issues in the data, the specified model, evaluation metrics, or bias during the actual deployment of the model. Although some biases are minor and not harmful, discriminatory biases tend to exacerbate certain inequalities with micro, macro, and meso implications. This section explains the various sources of algorithm biases discussed in the literature.

#### 3.2.1. Biases in Input to the Algorithm

Algorithmic bias often arises from the data used during input and training. Specifically, when algorithms learn from datasets, they can reinforce existing structural inequalities present in that data (Moussawi et al., 2024). These inequalities, which are embedded in society and culture, can be formalised by algorithms. Moreover, some datasets used to train models may not accurately represent the actual population, leading to discrimination or the underrepresentation of certain groups. Biases can also stem from outdated datasets, inaccurate or mismatched data. A system trained with insufficient data or datasets that do not accurately represent the study population is likely to recommend biased solutions. Additionally, if a model is either overfitted or underfitted, it may fall victim to the Garbage In, Garbage Out (GIGO) effect, becoming biased based on the training data. In some instances,

datasets collected from a single country are used to train global AI systems, which can cause problems when such systems are applied in different countries where the data may not be applicable (Moussawi et al., 2024).

### 3.2.2. Design Biases

Secondly, during algorithm development, bias may be introduced through feature or model selection, the objective function, evaluation metrics, or the choice of parameters for robustness or proxy variables correlated with protected characteristics (Moussawi et al., 2024). This form of bias is often categorised as technical bias or design biases. Design biases are fundamental algorithm biases that emanate not only from training data, but from model biases and method biases (Akter et al., 2022). Inaccurate modelling that is not consistent with underlying statistical and mathematical fundamentals or that does not include all the major variables can facilitate model biases. Roselli et al. (2019) argued that algorithm biases originate from proxy algorithm goals based on historical information, often ignoring different customer contexts. For example, a proxy goal of targeting young people as the primary buyers of certain products may cause biases in other markets where older populations are the main buyers. Literature concurs that algorithms inherit the biases of their creators and the datasets used to train them.

### 3.2.3. Application Biases

Thirdly, during the interpretation of results, bias may arise from misinterpreting the algorithm. In cases where an algorithm is implemented in a context different from that for which it was designed, context bias emerges; likewise, misinterpretation by the user can lead to interpretation bias. Biases during usage can result in unfair, discriminatory, and biased outcomes (Moussawi et al., 2024). Regardless of regulatory restrictions, pricing algorithms have been widely used by many retailers to gain an unfair advantage in capturing market share; hence, the application of these algorithms differs.

### 3.2.4. Contextual Biases

Contextual biases relate to biases that emanate from demographic and socio-cultural factors where histories of social discrimination are integrated in AI systems. Such historical and social biases embedded in the datasets have the potential to further intensify discrimination against historically disadvantaged populations, comprising people of different colour, social status, religion, gender, age group, subculture and many other social groups (Akter et al., 2022). Although much literature documents the unconscious development of algorithm biases, conscious inputting of biases based on gender, colour, or nationality cannot be disregarded.

### 3.2.5. Autonomy and Coordination of Algorithm Biases

The widespread adoption of algorithm pricing by competing companies can lead to algorithmically driven competitiveness where prices formulated by algorithms compete against one another, which can be harmful for consumers if price increases become detached from market demand (Nunan & Domenico, 2022). This scenario is common where algorithms of competing firms monitor or match each other's prices or where pricing algorithms are outsourced from the same system developer.

### 3.2.6. Exclusionary Biases and Manipulation Dark Patterns

Algorithm content curation and recommendations can also facilitate exclusionary biases where some customers are excluded from certain content, like promotions or price discounts, that may be vital for their purchasing savings. Facial recognition systems that tend to be less accurate for individuals with darker skin tones regularly lead to exclusionary biases and unfair results. Implicit and explicit manipulative dark patterns, which tend to exploit customers yet benefit suppliers through increased revenue creation, were also noted. In retail, some forced continuity subscriptions are applied when users sign up for a service with a free trial, extorting subscription purchases from clients continuously on a monthly, quarterly or yearly basis without explicit consent and without providing an option to opt out, hence making users economically vulnerable. However, exclusion content curation also assists in providing personalised pricing and services.

## 3.3. Managing Bias in AI

There is no single approach to resolving algorithm biases; however, Rosselli et al. (2019) argue that a combination of quantitative methods, business procedures, supervision, data review, assessments, and controlled experiments is essential for reducing algorithm biases. The authors contend that because most AI systems rely on complex black-box algorithms for decision-making, evaluation processes should focus on the input and output of the algorithm. First, the assumptions of the model must be validated with evidence regarding the validity of the selected numerical models, hypotheses, and the environmental impact of the developed system (Rosselli et al., 2019). The literature recommends the careful examination of data sources used to train algorithms in terms of representation, quality, and fairness, ensuring that women and minorities are proportionately represented as a measure to eliminate input data bias. Developers should ensure that datasets include balanced demographic representation and consider reweighting to correct imbalances of underrepresented groups (Bahangulu & Owusu-Berko, 2025).

The literature concurs on the need for transparency and accessible explanations for algorithmic decisions. Although some algorithms are black boxes, developers should try to use supervised and reinforcement learning, which offer better rationale for the decisions made. Literature recommends that decisions of algorithm systems should be explainable, transparent, fair, and organisations should ensure accountability of decisions made by these systems (Jakkula, 2020). Hence, the adoption and enforcement of ethical principles of fairness, accountability, transparency, and explainability. Explainable AI techniques provide insights into which factors influence an AI model's decisions; this improves the interpretation of the decisions and assists in the identification and management of algorithm biases. Through accountability, retailers should take responsibility for the outcomes produced by their algorithm pricing systems. Likewise, the use of fairness-aware machine learning techniques and conducting impact assessments before deploying AI systems assist in ensuring algorithms do not discriminate against certain minority groups of the population (Bahangulu & Owusu-Berko, 2025).

Akter et al. (2021) suggest that an AI model should address real-world problems; therefore, the expected outcomes of the AI system should be compared with a real surrogate to ensure scientific consistency. During the initial phase of developing the AI system, inconsistencies related to scientific, application, and stakeholder perspectives should be assessed. Training data must be vetted for accuracy, relevance, and currency, while guarding against manipulation and overly curated datasets. Akter et al. (2021) further suggested utilising available tools to detect and mitigate bias and validate system predictions, providing explanations for those predictions. Monitoring during AI system development is also crucial in identifying incomplete data, data divergence, and rare or unusual cases. Diversity in AI development, the use of testing teams, as well as trained AI bias auditors, to identify and mitigate bias in consumer AI applications, were also recommended as measures against algorithm bias.

Decisions made by AI systems should be understandable in terms of the input, output, and the functioning of each algorithmic building block and how it contributes to the outcome decision of the AI system. Company clients should be fully informed when a decision is informed by or is made based on AI algorithms, and robust data ethics frameworks must be integrated into AI governance strategies (Bahangulu & Owusu-Berko, 2025).

Organisations must implement bias detection methods, fairness-aware machine learning models, and continuous audits to minimise unintended consequences. Before the development of AI models, conducting a demographic parity analysis helps to assess if an AI system assigns similar probabilities of favourable outcomes across different demographic groups (Bahangulu & Owusu-Berko, 2025). This method assists in detecting and preventing algorithm biases. Whilst equalised odds

and disparate impact analysis assist in identifying discriminatory patterns and ensuring consistency (Bahangulu & Owusu-Berko, 2025). During the development of the AI model, bias-aware training techniques like adversarial debiasing and regularisation-based bias mitigation, where AI models are trained to minimise biased classification errors and where fairness constraints are added to the model during training, are crucial. Whilst AI can address biases after the development of an AI model, techniques like re-ranking methods, calibration-based fairness correction and thresholding techniques can be implemented.

Social norms influence reactions to price discrimination; hence the need for algorithm pricing strategies to incorporate social norms and accepted reference prices to avoid lower perceived fairness, reduced trust, decreased purchase intentions, and increased complaint behaviours (Garbarino & Maxwell, 2010).

Regular algorithm bias audits with fairness metrics, user-centric control interfaces that allow humans to modify outputs and the use of inclusive, diverse, representative data were also recommended as vital in managing algorithm biases (Abhadiomhen & Oyibo, 2025). Extant literature advocates for the importance of human oversight in automated decision-making, where AI recommendations are reviewed by human experts before finalisation. This enhances accountability in AI decision-making and allows management ultimate control (Bahangulu & Owusu-Berko, 2025).

### 3.4. Implications and Directions for Future Research

Algorithmic systems have become part of people's daily lives; hence, the assessment and management of algorithmic bias is a fundamental gap that should be explored soon for advancing trustworthy AI, prioritising human rights, enhancing sustainability and addressing societal concerns. Regular algorithm bias audits and transparency-enhancing approaches that analyse bias should be implemented throughout the entire algorithm pricing lifecycle. Transparency and explainability were proposed as the dominant remedy for managing biases. Price fairness perceptions are crucial for consumer repurchase intentions. Without proper governance and expert knowledge of how the adopted pricing algorithm was developed, retailers risk using pricing algorithms with inherent biases and, considering the high technical skills gap in systems development, most small to medium enterprises outsource already developed systems with embedded biases. Further research should conduct data access-enabled audits of live retail pricing algorithms to develop practical solutions.

## 4. Conclusion

The research sought to assess how algorithm pricing in retail is conceptualised, identify sources of algorithm bias and to determine best practices for managing algorithm biases in retail. Dynamic and personalised pricing were discussed as the major forms of algorithm pricing in the literature. Algorithm biases emanate from biases in input to the algorithm, design biases, application biases, contextual biases, autonomy and algorithm coordination biases, exclusionary and manipulation parameters. Algorithm biases can be managed through careful examination of data used to train models in terms of presentation, quality, relevance, accuracy and fairness. Transparency, explainability, regular algorithm audits and human oversight were cited as major ways of managing algorithm pricing biase.

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