AI for Pricing Decisions: A Two-Level Taxonomy of Applications

Ludovica Nardi, Andrea De Mauro
Luiss University, Viale Pola 12, Rome, Italy
ludovica.nardi@studenti.luiss.it
ademauro@luiss.it

Abstract

In an increasingly digitized and hypercompetitive market landscape, pricing is evolving from a static, cost-based process into a dynamic, strategic function powered by Artificial Intelligence (AI). Organizations are moving beyond traditional pricing models by leveraging real-time analytics, predictive modelling, and behavioural insights to enhance pricing decisions. AI enables large-scale automation and personalization of prices, allowing firms to adapt continuously to changes in demand, consumer behavior, and competitive signals. However, this shift also raises critical concerns regarding transparency, fairness, and algorithmic accountability—especially in consumer-facing markets, where price sensitivity and perceptions of justice directly influence trust and loyalty. This study shows how AI reshapes pricing across four impact areas—predictive modelling, real-time optimisation, behavioural adaptation, explainability and fairness—and, through a systematic literature review, distils a two-level taxonomy of AI applications in pricing. The findings demonstrate that AI-powered pricing enhances forecasting accuracy, enables granular and dynamic price optimization, and improves behavioural targeting through the integration of cognitive heuristics such as anchoring and loss aversion. These advantages, however, must be weighed against the growing risks of algorithmic opacity and perceived discrimination. These benefits must be carefully balanced against the increasing risks of algorithmic opacity and perceived discrimination, which can gradually undermine consumer trust. The study emphasises that AI is not merely a technological tool, but a transformative agent that reshapes market dynamics and redefines consumer expectations. As such, the adoption of transparent, explainable, and ethically aligned AI models is essential—not only to ensure compliance with emerging regulatory frameworks, but also to foster long-term consumer confidence and sustainable competitive advantage. The paper concludes by calling for interdisciplinary research to explore the longitudinal effects of AI-based pricing, ethical governance mechanisms, and the integration of social responsibility into algorithmic pricing strategies.

Keywords: Price Management; Behavioural Economics; Artificial Intelligence; Systematic Literature Review; Marketing

Paper type: Academic Research Paper

This is the preprint version of the paper published in *IFKAD25 Knowledge Insights: Exploring Knowledge Futures*

To cite this paper: Nardi, L., De Mauro, A. (2026). AI for Pricing Decisions: A Two-Level Taxonomy of Applications. In: *IFKAD25 Knowledge Insights: Exploring Knowledge Futures*. Lecture Notes in Networks and Systems, vol 1940. Springer, Cham, pp. 412–419. https://doi.org/10.1007/978-3-032-23684-5_47

1 Introduction

The increasing digitalization of global markets has profoundly transformed pricing, elevating it from a rule-based administrative function to a strategic, data-driven lever. Once grounded in cost-plus logic or fixed price lists, pricing is now shaped by real-time analytics, algorithmic models, and, increasingly, behavioural insights. More recently, Artificial Intelligence (AI) has become a prominent driver of this transformation. AI empowers organizations to automate pricing determinations while simultaneously enhancing these processes through predictive capabilities, contextual responsiveness, and psychological attunement (Prithi & Tamizharasi, 2025; Li et al., 2022).

In recent years, the literature has highlighted growing interest in the strategic potential of AI applied to pricing. Erdmann et al. (2024) propose a framework for evaluating AI-based pricing systems through the lenses of sustainability, regulatory alignment, and economic efficiency, underlining the importance of predictive accuracy and customer value creation. Gerlick and Liozu (2020) delve into the ethical and legal implications of algorithmic personalised pricing, emphasizing that perceptions of fairness and transparency are critical for consumer acceptance. This transition—from manual segmentation to algorithmically optimised targeting—reflects a broader shift toward AI-driven value extraction and reinforces the need for transparency and explainability in automated systems.

Agarwal et al. (2024) stress that algorithmic opacity may hinder not only regulatory compliance but also managerial capacity to interpret and govern pricing logic. In response, tools from the field of Explainable Artificial Intelligence (XAI)—such as SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME)—help reconstruct pricing rationale, thereby enhancing interpretability and trust (Peng et al., 2023). Concurrently, the integration of behavioural economics into AI models is gaining momentum. Shan and Li (2025) demonstrate that cognitive biases such as anchoring and loss aversion significantly affect price perception and can be embedded in intelligent systems to reinforce personalisation. In the tourism sector, for example, Nguyen and Nguyen (2025) show how reinforcement learning-based dynamic pricing algorithms can adjust in real time to consumer preferences, improving financial performance.

This study contributes to this interdisciplinary dialogue by synthesising insights from machine learning, behavioural economics, and algorithmic governance to explore how AI is reshaping pricing architectures. Through a systematic literature review, four thematic dimensions are identified through which AI impacts pricing decisions: predictive modelling, real-time optimisation, behavioural adaptation, explainability and fairness.

The remainder of the paper is structured as follows: Section 2 outlines the theoretical background, with particular attention to AI methodologies and behavioural pricing theories. Section 3 describes the research methodology, including the literature review strategy and the development of the taxonomy. Section 4 presents the key findings, organised around the four thematic dimensions. Finally, Section 5 offers theoretical, managerial, and policy-related implications and suggests avenues for future research.

2 Theoretical Background

This section outlines the interdisciplinary theoretical foundations that inform the integration of Artificial Intelligence (AI) in pricing systems. The focus is placed on the convergence of computational methods, behavioural economics, and governance frameworks. Special attention is given to the mechanisms through which AI technologies shape, and are shaped by, consumer psychology and regulatory imperatives. The section is structured in two interrelated subsections: AI methodologies in pricing, and behavioural pricing theories.

2.1 AI Methodologies in Pricing

Artificial Intelligence (AI) has introduced new paradigms in pricing by enabling firms to shift from reactive, rule-based strategies to proactive, data-driven optimisation (Duan et al., 2019; Davenport et al., 2020). Among the most widely adopted methodologies are supervised learning, unsupervised learning, and reinforcement learning. Supervised learning techniques—such as eXtreme Gradient Boosting (XGBoost) and Long Short-Term Memory (LSTM) networks—are commonly used to forecast demand, estimate price elasticity, and analyse market dynamics based on historical, behavioural, and contextual data (Ma & Sun, 2020; Kumar et al., 2019). These models support a wide array of pricing applications, including dynamic price adjustment, personalised promotions, and contextual targeting. In AI-powered environments like e-commerce, these capabilities allow companies to adapt offers in real time, increasing pricing precision and relevance (Huang & Rust, 2021; Corbo et al., 2022). Unsupervised learning, typically implemented through clustering algorithms, enables the identification of latent customer segments without the need for predefined labels. These clusters serve as a foundation for differentiated pricing strategies based on behavioural profiles and contextual relevance (Erevelles et al., 2016; Sestino & De Mauro, 2021). In practice, this enables more accurate segmentation and microtargeting, especially in environments where consumer preferences are dynamic and unstructured. Reinforcement learning offers a more autonomous and adaptive approach, where pricing algorithms learn over time by interacting with consumers and market signals. These models adjust prices dynamically, responding to real-time feedback such as user behaviour, conversion rates, and competitive movements (Guda & Subramanian, 2019; Campbell et al., 2020). Applications of reinforcement learning are particularly effective in scenarios such as surge pricing, auction-based platforms, and real-time bidding. As these AI-driven methodologies advance, they bring growing concerns about algorithmic opacity and the need for explainability. Tools from the field of Explainable Artificial Intelligence (XAI)—including SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME)—enable stakeholders to interpret, audit, and validate automated pricing decisions (Peng et al., 2023; Davenport et al., 2020). These tools play a crucial role in maintaining transparency, regulatory compliance, and consumer trust in complex algorithmic environments.

2.2 Behavioural Pricing Theories

Behavioural pricing theories are grounded in the notion that consumers do not respond to prices in fully rational ways, but are influenced by heuristics, cognitive biases, and emotional factors. Integrating these principles into AI-supported pricing systems enables the development of more persuasive, adaptive, and personalised strategies (Shan & Li, 2025; Huang & Rust, 2021). Among the most relevant biases are the anchoring effect, whereby consumers evaluate prices relative to an initial reference point, and loss aversion, which amplifies the perceived impact of a price increase compared to an equivalent discount. These psychological mechanisms are increasingly embedded into machine learning models, allowing prices to be tailored to individual thresholds of acceptability (Ma & Sun, 2020; Kumar et al., 2019). In digital environments, such approaches manifest through techniques like charm pricing (e.g., €9.99 instead of €10), urgency framing, and perceptual customisation of offers. The literature also highlights that the application of AI in personalised pricing must balance persuasive effectiveness with ethical and reputational considerations. Corbo et al. (2022) emphasise the importance of transparent models capable of explaining the rationale behind price recommendations. Excessive opacity can generate perceptions of manipulation or discrimination, undermining consumer trust and diminishing purchase intent (Davenport et al., 2020; Erevelles et al., 2016). Moreover, AI technologies allow real-time monitoring of consumer behavioural responses, enabling dynamic adaptation of pricing strategies. In particular, reinforcement learning models can learn which psychological patterns are most effective for each customer segment, thus enhancing the precision of personalisation (Campbell et al., 2020; Guda & Subramanian, 2019). Finally, the adoption of Explainable AI (XAI) approaches is equally crucial in behavioural pricing: explaining not just what is proposed, but why, can significantly increase consumer acceptance of AI-driven recommendations and reduce psychological resistance (Sestino & De Mauro, 2021; Duan et al., 2019). In this sense, algorithmic governance should not be viewed solely as a regulatory constraint, but as a strategic lever for building long-term relationships with increasingly fairness-sensitive customers.

3. Methodology

This research adopts a Systematic Literature Review (SLR) methodology as a structured, transparent, and replicable approach to synthesising existing knowledge, consistent with best practices in management and artificial intelligence adoption research (De Mauro et al., 2019; Duan et al., 2019). Unlike narrative reviews, often characterised by a higher degree of subjective interpretation, SLRs minimise bias through the application of rigorous protocols and standardised procedures. To ensure methodological transparency, the review process was aligned with the PRISMA framework (Moher et al., 2009), which provides a structured guideline for article identification, screening, eligibility assessment, and inclusion. The PRISMA method is widely recognised for enhancing the transparency, replicability, and methodological rigour of systematic reviews across management, information systems, and data analytics research (De Mauro et al., 2019). The methodological approach was articulated into three main phases: (i) selection of the article corpus; (ii) extraction and categorisation of article content; (iii) analysis of AI-related pricing dimensions through structured content analysis. This multi-layered process ensured both analytical depth and procedural replicability, enabling the development of a dual-level taxonomy that illustrates how artificial intelligence technologies are reshaping pricing decision-making across predictive, behavioural, and ethical dimensions.

3.1 Review Scope and Selection Criteria

The scope of this review was defined at the intersection between AI-driven pricing models, behavioural pricing mechanisms, and the ethical and regulatory challenges associated with algorithmic governance. The literature search was conducted exclusively using the Scopus academic database by employing a structured query:

((TITLE (price) OR TITLE (pricing)) AND (TITLE ("artificial intelligence") OR TITLE (ai) OR TITLE ("analytics"))) AND PUBYEAR > 2009 AND PUBYEAR < 2026 AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "cp")) AND (LIMIT-TO (LANGUAGE , "English"))

Because this string already limits results to English-language journal articles (“ar”) and conference papers (“cp”) published between 2010 and 2025, several inclusion criteria were operationalised at the search stage. To ensure relevance and quality, four inclusion criteria were applied: (i) peer-reviewed journal articles or conference papers written in English; (ii) publication years 2010-2025; (iii) explicit focus on AI applications to pricing with managerial, behavioural, strategic, ethical, or regulatory implications; and (iv) availability of the full text. Studies were excluded when they (a) addressed purely technical AI issues without a pricing or managerial dimension, (b) reported single, non-generalisable case studies, or (c) lacked retrievable full texts.

In the first phase, a preliminary screening was conducted based solely on the titles and abstracts of the identified documents. As a result of the initial bibliographic search conducted through Scopus using a structured query string, a total of 337 contributions were identified. A first screening phase was carried out to filter out articles that were not relevant to the scope of the research, leading to the exclusion of 237 contributions that did not align with the intended research domain. A refined set of 100 articles was then subjected to a deeper review, with a focus on the presence of specific keywords, thematic alignment with the field of AI in pricing, and overall methodological robustness. This qualitative assessment led to the final selection of 52 contributions, which represented the most relevant and insightful works for the purposes of the structured content analysis and taxonomy elaborated in the study. Figure 1 summarizes the resulting article selection process.

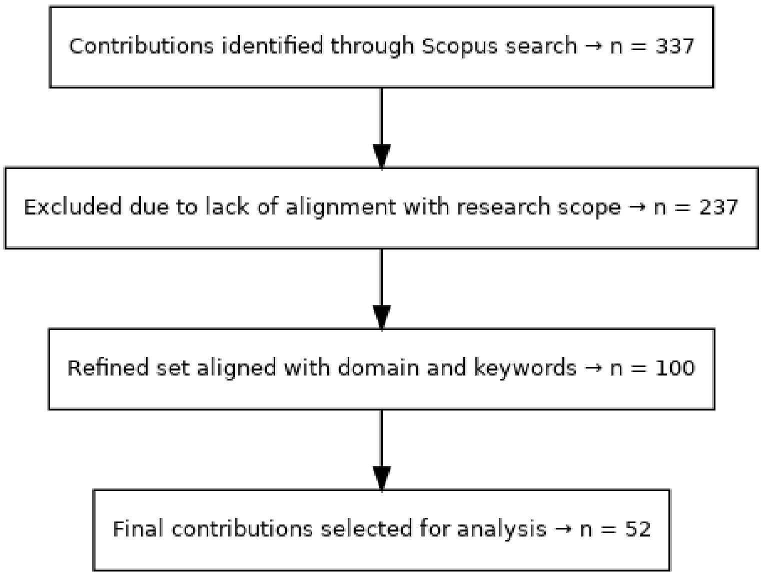

Figure 1: Funnel diagram of the article selection process.

3.2 Structured content analysis

Following the article selection phase, a Structured Content Analysis was conducted to classify the main pricing mechanisms and themes identified across the reviewed articles. Inspired by the methodological approach proposed by Kohlegger, Maier, and Thalmann (2009), a human-coding procedure was used. Key concepts were grouped into recurring thematic patterns through an iterative categorization process, which resulted in the four dimensions shown in Table 1. In the taxonomy, each dimension represents a high-level impact area; within every impact area, we further identified recurrent use-case scenarios that specify how AI supports pricing practice. This method enabled the development of a coherent and replicable taxonomy, systematically capturing the strategic, behavioural, operational, and ethical dimensions underpinning AI applications in pricing systems.

Impact area	Papers (n)	Share of corpus	Representative keywords
Predictive Modelling	20	39%	demand forecast, price elasticity, time-series

Real-Time Optimisation	11	21%	dynamic pricing, surge, RL
Behavioural Adaptation	8	15%	anchoring, loss aversion, personalisation
Explainability and Fairness	13	25%	SHAP, LIME, transparency

Table 1. Summarized output of the structured content analysis: impact-area clusters, document count, corpus share and representative keywords.

4. Findings and Discussion

This section discusses the key findings, organised around the four impact areas and their associated use-case scenarios, as identified in this study. Each branch of the taxonomy, shown in Figure 2, reflects a distinct pathway through which Artificial Intelligence (AI) is reshaping pricing mechanisms across industries.

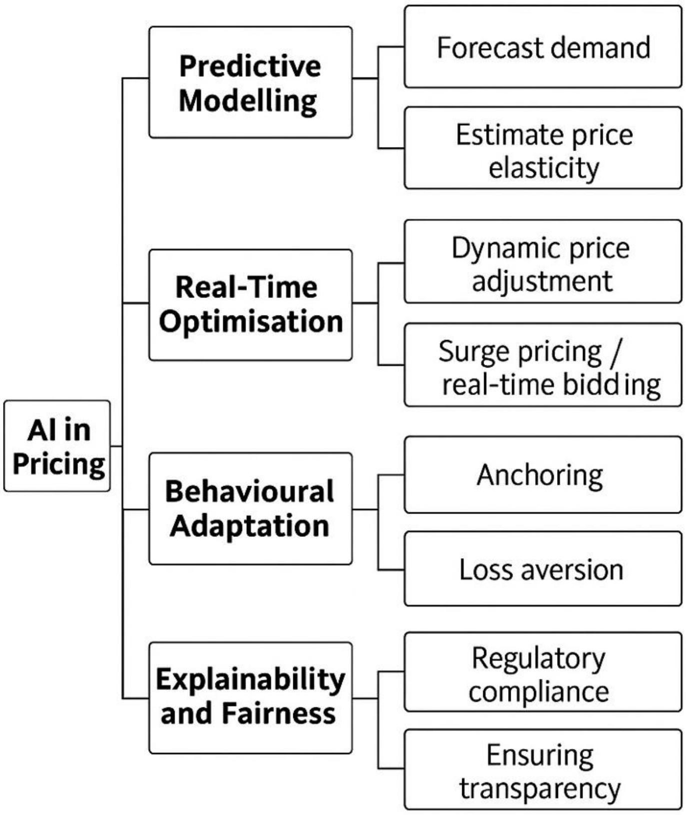

Figure 2: Two-level taxonomy of AI in pricing: impact areas (Level 1) and illustrative use-case scenarios (Level 2).

4.1 Predictive Modelling

Predictive modelling refers to the use of supervised learning algorithms to anticipate demand trends, forecast price elasticity, and optimise pricing strategies based on historical and contextual data. Techniques such as Extreme Gradient Boosting (XGBoost) and Long Short-Term Memory networks (LSTM) have proven highly effective in this area (Ma & Sun, 2020; Kumar et al., 2019). Applications in industries like e-commerce and transportation demonstrate the strategic advantage of leveraging demand forecasting to drive dynamic price adjustments (Li et al., 2022; Nguyen & Nguyen, 2025). Moreover, research indicates that predictive models increasingly incorporate external variables—such as competitor behaviour and macroeconomic indicators—to refine their accuracy and business relevance (Duan et al., 2019).

4.2 Real-Time Optimisation

Real-time optimisation focuses on deploying reinforcement-learning (RL) algorithms that enable dynamic price adjustments and surge-pricing or real-time bidding schemes in response to market signals. This approach is particularly critical in sectors where supply and demand conditions fluctuate rapidly, such as tourism and ride-sharing (Guda & Subramanian, 2019; Nguyen & Nguyen, 2025). For instance, dynamic pricing algorithms allow companies to optimise occupancy rates and revenue by adapting to real-time consumer behaviour and booking patterns (Sidlauskiene, Joye, & Auruskeviciene, 2023). Recent advances in RL not only improve financial performance but also enhance customer satisfaction by offering contextually appropriate prices (Peng, Peng, & Xu, 2024).

4.3 Behavioural Adaptation

Behavioural adaptation highlights how AI models integrate cognitive biases into pricing strategies, aligning offers with consumer decision-making heuristics. Anchoring effects, loss aversion, and charm pricing are increasingly embedded within algorithmic designs (Huang & Rust, 2021; Erevelles, Fukawa, & Swayne, 2016). For example, charm pricing techniques—such as setting a price at €4.99 instead of €5.00—have been shown to significantly affect purchase intention (Jeong, Choo, & Yoon, 2021). Moreover, recent studies emphasise the role of behavioural targeting enhanced by AI in personalising price offers to individual cognitive profiles, thereby optimising perceived value and conversion rates (Prithi & Tamizharasi, 2025; Shan & Li, 2025).

4.4 Explainability and Fairness

The final dimension addresses the growing need for transparency and ethical safeguards in AI-based pricing systems. Explainable Artificial Intelligence (XAI) frameworks, such as SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME), are increasingly adopted to provide understandable rationales for algorithmic pricing decisions (Sestino & De Mauro, 2021; Davenport et al., 2020). This concern is particularly critical in pricing contexts where customers may perceive algorithmic adjustments as unfair or opaque (Peng, Peng, & Xu, 2023). Furthermore, regulatory frameworks like the General Data Protection Regulation (GDPR) are compelling firms to design pricing algorithms that are transparent, accountable, and free from discriminatory practices (Gerlick & Liozu, 2020; Elyakim, 2025). Research suggests that explainability not only supports legal compliance but also enhances consumer trust and loyalty, ultimately contributing to a more sustainable competitive advantage (Raphael et al., 2024; Zhou et al., 2025).

5. Conclusions and Implications

The present study contributes to the growing body of literature at the intersection of AI, behavioural economics, and pricing strategy by proposing an integrated framework that describes the four impact areas of AI in pricing and how they are linked to concrete use-case scenarios. It enriches existing theory by demonstrating how AI not only automates pricing decisions but actively co-shapes market dynamics and consumer behaviour. In line with Erdmann et al. (2024), the analysis highlights that ethical and sustainability dimensions must now be considered core criteria in evaluating AI-enhanced pricing models.

From a managerial perspective, the paper underscores that AI-powered pricing systems represent both a technological opportunity and an organisational challenge. Managers must not only select appropriate AI techniques—such as Extreme Gradient Boosting (XGBoost) for demand forecasting or Reinforcement Learning (RL) for real-time price adjustments—but also ensure their alignment with strategic objectives and ethical principles. As demonstrated by Harley-Davidson's experience with AI-driven campaign optimisation (Power, 2017), pricing engines achieve superior results when designed to iteratively learn from behavioural and contextual data. Furthermore, for small and medium-sized enterprises (SMEs), a focused approach is critical: prioritising specific high-impact pricing applications over generic AI adoption optimises resource utilisation and strategic fit.

From a regulatory standpoint, the study reinforces the urgent need to develop coherent legal frameworks capable of addressing the opacity, discrimination risks, and asymmetries of power generated by algorithmic pricing systems. Gerlick and Liozu (2020) caution that unchecked personalised pricing can erode consumer trust and exacerbate social inequalities. In this regard, the integration of Explainable Artificial Intelligence (XAI) tools—such as SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME)—should be mandated for consumer-facing algorithms, particularly when price discrimination practices are involved. While initiatives like the European Union's AI Act and the General Data Protection Regulation (GDPR) lay critical foundations, issues related to enforcement and practical interpretability remain significant challenges.

The evolution of AI-driven pricing systems presents several promising avenues for future research. Empirical studies are needed to assess how different AI techniques—such as Reinforcement Learning (RL) and Explainable Artificial Intelligence (XAI)—influence consumer trust and long-term loyalty in dynamic pricing contexts (Sestino & De Mauro, 2021; Davenport et al., 2020). As new tools for algorithmic transparency are developed, it becomes increasingly important to evaluate not only their technical performance but also their perceptual impact on consumers. A relevant direction concerns the interaction between AI-based pricing and sustainability objectives. As highlighted by Raphael et al. (2024), the integration of AI in price management must increasingly incorporate environmental and social governance (ESG) criteria to ensure responsible innovation. Investigating how pricing algorithms can be optimised not only for profit maximisation but also for sustainable consumption behaviours represents a key opportunity for future studies. Interdisciplinary research is also essential to understand the broader socio-economic consequences of AI-powered price personalisation. Insights from behavioural economics, digital ethics, and consumer protection law can contribute to designing algorithms that balance personalisation with fairness and inclusivity (Gerlick & Liozu, 2020; Elyakim, 2025). Finally, long-term empirical investigations are necessary to explore the organisational capabilities and cultural transformations required for the successful implementation of AI-based pricing. We corroborate recent contributions (De Mauro & Pacifico, 2024) stressing that technological adoption alone is insufficient without corresponding changes in data governance, leadership strategies, and continuous learning practices. By addressing these areas, future research can enhance the effectiveness of AI-based pricing systems while contributing to the development of a more transparent, ethical, and sustainable digital economy.

Ethics Declaration

This study did not involve human participants, personal data, or ethically sensitive content requiring formal clearance. No ethical approval was necessary.

AI Declaration

This paper was developed with the support of an AI-based assistant for drafting and language refinement. All content has been reviewed and validated by the authors to ensure academic accuracy, integrity, and originality.

References

Agarwal, R., Kremer, A., Kristensen, I. and Luget, A. (2024) 'The future of generative AI in banking: How generative AI can help banks manage risk and compliance', McKinsey & Company. Available at: https://www.mckinsey.com

Bacconi, A. (2021) Machine Learning Use in Marketing: A General Taxonomy, MSc Thesis, HEC Paris and École Polytechnique.

Campbell, C., Sands, S., Ferraro, C., Tsao, H. Y. and Mavrommatis, A. (2020) 'From data to action: How marketers can leverage AI', Business Horizons, 63(2), pp. 227–243.

Caro, F. and de Tejada Cuenca, A.S. (2023) 'Believing in analytics: Managers' adherence to price recommendations from a DSS', Manufacturing and Service Operations Management, 25(3), pp. 1291–1309. https://doi.org/10.1287/msom.2022.1166

Corbo, L., Costa, S. and Dabi, M. (2022) 'The evolving role of artificial intelligence in marketing: A review and research agenda', Journal of Business Research, 128, pp. 187–203.

De Mauro, A. and Pacifico, M. (2024) The Financial Times Guide to Data-Driven Transformation: Maximise Business Value with Data Analytics. 1st edn. London: FT Publishing International.

De Mauro, A., Greco, M. and Grimaldi, M. (2019) ‘Understanding Big Data Through a Systematic Literature Review: The ITMI Model’, International Journal of Information Technology and Decision Making, 18(4).

Davenport, T., Guha, A., Grewal, D. and Bressgott, T. (2020) ‘How artificial intelligence will change the future of marketing’, Journal of the Academy of Marketing Science, 48, pp. 24–42.

Duan, Y., Edwards, J.S. and Dwivedi, Y.K. (2019) ‘Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda’, International Journal of Information Management, 48, pp. 63–71.

Elyakim, N. (2025) ‘Bridging expectations and reality: Addressing the price-value paradox in teachers’ AI integration’, Education and Information Technologies. https://doi.org/10.1007/s10639-025-13466-z

Erdmann, A. et al. (2024) ‘Pricing powered by artificial intelligence: An assessment model for the sustainable implementation of AI-supported price functions’, Informatica, 35(3), pp. 529–556. https://doi.org/10.15388/24-INFOR559

Erevelles, S., Fukawa, N. and Swayne, L. (2016) ‘Big Data consumer analytics and the transformation of marketing’, Journal of Business Research, 69(2), pp. 897–904.

Gerlick, J.A. and Liozu, S.M. (2020) ‘Ethical and legal considerations of artificial intelligence and algorithmic decision-making in personalized pricing’, Journal of Revenue and Pricing Management, 19(2), pp. 85–98. https://doi.org/10.1057/s41272-019-00225-2

Guda, H. and Subramanian, U. (2019) ‘Your Uber is arriving: Managing on-demand workers through surge pricing, forecast communication, and worker incentives’, Management Science, 65(5), pp. 1995–2014.

Huang, M.H. and Rust, R.T. (2021) ‘A strategic framework for artificial intelligence in marketing’, Journal of the Academy of Marketing Science, 49(1), pp. 30–50.

Jeong, H.-E., Choo, H.J. and Yoon, N. (2021) ‘Price fairness perception on the AI algorithm pricing of fashion online platform’, Journal of the Korean Society of Clothing and Textiles, 45(5), pp. 892–904. https://doi.org/10.5850/JKSCT.2021.45.5.892

Kohlegger, M., Maier, R. and Thalmann, S. (2009) ‘Understanding maturity models: Results of a structured content analysis’, Proceedings of I-KNOW ’09 and I-SEMANTICS ’09, 2-4 September, Graz, Austria.

Kumar, V., Rajan, B., Venkatesan, R. and Lecinski, J. (2019) ‘Understanding the role of artificial intelligence in personalized engagement marketing’, California Management Review, 61(4), pp. 135–155.

Li, Y. et al. (2022) ‘Pricing strategies of AI-enabled and regular products’, IEEE International Conference on Industrial Engineering and Engineering Management, pp. 1056–1060. https://doi.org/10.1109/IEEM55944.2022.9989923

Ma, L. and Sun, B. (2020) ‘Machine learning and AI in marketing – Connecting computing power to human insights’, International Journal of Research in Marketing, 37(3), pp. 481–504.

Moher, D., Liberati, A., Tetzlaff, J. and Altman, D.G. (2009) ‘Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement’, BMJ (Online), 339(7716), pp. 332–336. https://doi.org/10.1136/bmj.b2535

Nguyen, T.T.N. and Nguyen, T.K.T. (2025) ‘Perceptions of AI-driven dynamic pricing strategies and their financial impact on Vietnamese tourism companies’, Journal of Information Systems Engineering and Management, 10(3S), Article 367. https://doi.org/10.52783/jisem.v10i3s.367

Peng, X., Peng, X. and Xu, D. (2023) 'Why users accept discriminatory pricing: The roles of AI agent's presence and explanation', Proceedings of the International Conference on Information Systems (ICIS).

Peng, X., Peng, X. and Xu, D. (2024) 'Does AI disclosure in discriminatory pricing backfire? The moderating role of price sensitivity and explanation for price differences', Proceedings of the Annual Hawaii International Conference on System Sciences.

Power, B. (2017) 'How Harley-Davidson used artificial intelligence to increase New York sales leads by 2,930%', Harvard Business Review. Available at: https://hbr.org/2017/05/how-harley-davidson-used-predictive-analytics-toincrease-new-york-sales-leads-by-2930

Prithi, M. and Tamizharasi, K. (2025) 'The future of retail pricing: AI-powered optimization and customization', Journal of Information Systems Engineering and Management, 10(5S), Article 668. https://doi.org/10.52783/jisem.v10i5s.668

Raphael, J. et al. (2024) 'Leveraging artificial intelligence and blockchain to stabilize rice price fluctuations in DKI Jakarta, Indonesia', International Conference on Intelligent Cybernetics Technology and Applications (ICICyTA). https://doi.org/10.1109/ICICYTA64807.2024.10913139

Sestino, A. and De Mauro, A. (2021) 'Leveraging artificial intelligence in business: Implications, applications and methods', Technology Analysis & Strategic Management, 1–14.

Shan, Y. and Li, R.Y.M. (2025) 'The impact of AI recommendation's price and product accuracy on customer satisfaction: SEM-SOR theoretical approach', Current Psychology. https://doi.org/10.1007/s12144-025-07456-0

Sidlauskiene, J., Joye, Y. and Auruskeviciene, V. (2023) 'AI-based chatbots in conversational commerce and their effects on product and price perceptions', Electronic Markets. https://doi.org/10.1007/s12525-023-00633-8

Wang, J., Zhang, B. and Liu, J. (2024) 'Effect of carbon price fluctuation on shore power system: A risk transmission analytics model', Environment, Development and Sustainability. https://doi.org/10.1007/s10668-024-05551-z

Xu, Y., Wang, X. and Yu, H. (2024) 'Research on pricing decisions optimization algorithm of fresh agricultural product supply chain under the background of artificial intelligence', Lecture Notes on Data Engineering and Communications Technologies, pp. 389–402. https://doi.org/10.1007/978-981-97-1979-2_32

Zhou, W. et al. (2025) 'Manufacturer's encroachment strategies when facing the retail platform with AI-driven pricing', Computers and Industrial Engineering, 185, 111003. https://doi.org/10.1016/j.cie.2025.111003

Zuiderveen Borgesius, F. and Poort, J. (2017) 'Online price discrimination and EU data privacy law', Journal of Consumer Policy, 40(3), pp. 347–366. https://doi.org/10.1007/s10603-017-9352-z