Journal of
Theoretical and Applied Electronic Commerce Research

MDPI

Systematic Review

AI-Based Dynamic Pricing: A Cross Industry Bibliometric Review of Trends, Challenges, and Future Directions

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Abstract

Artificial intelligence has transformed dynamic pricing by enabling firms to forecast demand more accurately, respond to market uncertainty, and optimize prices in real time. Existing reviews remain fragmented, typically focusing on a single industry or on isolated methodological streams like reinforcement learning or time-series forecasting. To address this gap, this study provides a comprehensive, cross-industry synthesis of AI-based Dynamic Pricing through a systematic bibliometric analysis of 1301 Scopus-indexed publications from January 2005 to August 2025. E-commerce and digital platforms serve as the study's central analytical lens because they frequently combine real-time transactional data, rapid price adjustment, customer-level behavioral information, platform competition, and algorithmic repricing. The analysis also extends to other digitally mediated pricing environments, including energy, mobility, electric-vehicle charging, hospitality, transportation, and retail, allowing the study to examine how methods, adoption patterns, and governance concerns vary across sectors. Using VOSviewer and CiteSpace, the study maps the intellectual structure of the field and identifies eight major research clusters. The findings reveal a clear methodological shift from rule-based and econometric approaches toward deep learning, multi-agent reinforcement learning, and simulation-driven decision systems. They also show that data-intensive and platform-mediated sectors are becoming increasingly prominent in the development and application of advanced AI-based pricing methods, while established revenue-management domains such as airlines and hospitality remain important foundations of the field. Building on these patterns, the study outlines future research opportunities centered on interpretable and uncertainty-aware pricing models, ethical and fair pricing mechanisms, and cross-industry transfer of methods and regulatory practices. This synthesis provides a structured foundation for advancing theory, methodology, and practice in AI-based DP.

Keywords: dynamic pricing; artificial intelligence; machine learning; deep reinforcement learning; bibliometric analysis

Check for updates

Academic Editor: Mirjana Pejić-Bach

Received: 2 March 2026
Revised: 2 August 2026
Accepted: 10 August 2026
Published: 19 August 2026

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1. Introduction

Pricing is a central managerial tool that affects consumer behavior, firm competitiveness, and profitability [1]. In the digital economy, static pricing strategies have increasingly been supplemented or replaced by data-driven mechanisms that respond to changes in demand, competition, and market conditions [2]. Dynamic pricing (DP) refers to the adjustment of product or service prices in response to changes in demand, supply, competition, or

customer-related factors [3,4]. The development of DP is commonly associated with airline revenue management in the early 1990s, particularly American Airlines' emphasis on selling the appropriate product to the appropriate customer at the appropriate time and price [5]. DP has since been applied across hospitality, retail, e-commerce, transportation, and energy [6]. E-commerce/digital platforms provide a particularly relevant context because they combine real-time data, rapid competitor monitoring, automated price adjustments, and high customer visibility of price changes. In these environments, dynamic pricing involves not only revenue and operational decisions but also concerns related to competition, customer trust, fairness, and managerial oversight.

DP can support revenue management, supply–demand balancing, customer segmentation, and inventory management [7]. However, automated and personalized price adjustments also raise concerns about perceived fairness, transparency, customer acceptance, and managerial oversight. In e-commerce, platforms such as Amazon adjust prices in response to competitor prices, customer browsing behavior, and inventory availability [8]. In travel and hospitality, pricing algorithms adjust fares and room rates according to timing, seasonality, and booking patterns [9].

Traditional DP systems relied primarily on predefined rules and econometric demand models, which can be limited in complex and rapidly changing online markets [10]. Artificial intelligence (AI) has expanded the analytical, predictive, and adaptive capabilities available for DP [11]. Machine learning (ML), deep learning (DL), and reinforcement learning (RL) have been applied to demand forecasting, pattern recognition, and sequential pricing decisions using behavioral, transactional, and contextual data [12]. These models can identify nonlinear relationships, learn from feedback, and support the estimation of demand and customer willingness to pay [13]. In e-commerce, AI-based dynamic pricing systems can use browsing, transactional, and market data to support individualized or context-sensitive pricing [12]. These applications also raise governance concerns regarding fairness, transparency, managerial oversight, and unintended algorithmic outcomes [14].

DP research spans operations management, marketing, economics, and computer science [15,16]. Tomitza et al. [12] reviewed AI-based dynamic pricing methods in e-commerce and classified the literature by activity level, application procedure, data foundation, and algorithm. The review identified challenges in algorithm selection and integration with existing business processes. Wang et al. [17] reviewed developments in DP research across industries, including the growing use of AI, big data, and behavioral approaches. Together, these reviews indicate that AI-based dynamic pricing research remains fragmented across methods, data requirements, implementation contexts, and industries.

Bibliometric studies have also examined the development of DP research. Hu et al. [18] reviewed dynamic electricity pricing programs in the United States and Europe, emphasizing implementation issues related to policy coordination, customer engagement, and measurement. Poláček et al. [4] conducted a bibliometric analysis of 153 Web of Science indexed studies on DP in e-commerce, examining publication growth, research areas, citation patterns, and thematic trends. Goli and Haghighinasab [3] mapped the broader DP literature using citation and clustering analyses. Collectively, these studies document the development of DP research but focus on selected sectors, general DP trends, or broad bibliometric indicators. They provide limited cross-industry evidence on the development of AI-based dynamic pricing techniques and their relationships with specific application domains.

Three related gaps emerge in the literature. First, limited bibliometric research has specifically examined the development of AI-based dynamic pricing, including ML, DL, and RL. Second, the concentration of existing reviews on individual industries or pricing mechanisms limits cross-industry comparison of AI-based dynamic pricing methods. Third, governance-related themes, including fairness, transparency, accountability, and managerial

oversight, have received limited attention in bibliometric assessments of AI-based DP. An integrated cross-industry synthesis linking AI methods, pricing applications, industry contexts, and governance-related themes therefore remains limited.

To address these gaps, this study presents a bibliometric review of AI-based dynamic pricing research. It combines performance analysis, science mapping, keyword and cluster analysis, and thematic coding of AI techniques, applications, and industries. This design examines the field's intellectual structure, thematic development, methodological patterns, and application contexts over time.

The study addresses the following research questions:

RQ1: What are the bibliometric characteristics and trends of AI-based DP research?

RQ2: What are the dominant research themes and emerging topics in AI-based DP?

RQ3: What are the key challenges and research gaps in AI-based DP?

RQ4: How have AI-based DP techniques developed across industries, and which AI models have dominated their applications over time?

This study maps the intellectual structure and thematic development of AI-based dynamic pricing research across industries, with particular attention to e-commerce/digital platforms. It links bibliometric patterns with AI techniques, application domains, and governance-related themes to clarify the structure and development of the literature.

For e-commerce research, the cross-industry synthesis extends the systematization of AI-based DP methods provided by Tomitza et al. [12] in two ways. First, e-commerce/digital-platform studies provide a reference point for comparing how AI-based dynamic pricing methods are applied across other industries. Second, the clusters associated with e-commerce and online marketplaces identify research themes related to automated repricing, platform competition, personalization, forecasting, and operational integration (Section 5.2).

2. Conceptual Background

AI-based DP can be understood through two connected dimensions: the evolution of pricing strategies and the integration of AI into pricing decision systems. DP has evolved from manual and rule-based adjustments toward automated, data-driven mechanisms, while AI has expanded firms' ability to analyze market data and support real-time pricing decisions. This section summarizes the conceptual foundations of dynamic pricing and AI-based pricing and explains their intersection in contemporary business environments.

Several review studies have examined dynamic pricing from domain-specific or method-focused perspectives. Yin and Han [19], for example, focus on reinforcement learning based pricing models in e-commerce, offering valuable algorithmic insights but limited coverage of transportation, hospitality, or energy systems. Chen and Folly [20] review AI-based pricing for EV charging and discharging, with an emphasis on demand forecasting and scheduling in energy markets. In the advertising domain, Tan et al. [21] examine time-series forecasting models for digital signage pricing, while Hao et al. [22] provide a systematic review of dynamic pricing in electricity markets centered on tariff design, demand response, and fairness. While these studies contribute important domain-specific insights, their narrow scope limits broader understanding of how AI-based dynamic pricing methods compare and transfer across industries.

2.1. Dynamic Pricing

Dynamic pricing (DP) is a pricing strategy in which firms adjust prices in real or near-real time in response to market conditions, demand, competitor actions, inventory levels, and consumer behavior [23]. Unlike fixed pricing, DP allows firms to revise prices as market conditions change [24,25]. DP has developed from time-based approaches, such as time-of-day and seasonal pricing, to algorithmic systems that use machine learning (ML)

to process large volumes of data and support automated pricing decisions. DP generally aims to improve revenue outcomes by balancing supply and demand while accounting for willingness to pay, competitor prices, and market conditions [7]. As markets become more competitive and consumer behavior more complex, firms increasingly use DP to respond to changing market conditions [26].

The evolution of DP across industries demonstrates its growing importance in modern business operations. Airlines pioneered the widespread adoption of DP in the 1980s following deregulation, adjusting ticket prices based on demand, booking patterns, seat availability, and time until departure [27]. The hotel industry quickly followed suit, implementing revenue management systems that adjust room rates based on occupancy levels, local events, seasonal demand, and competitors' pricing strategies. DP has since become a defining feature of e-commerce/digital platforms, where firms such as Amazon adjust prices thousands of times daily in response to the same competitive and demand signals noted above [28]. The ride-sharing industry, especially companies like Uber and DiDi, has popularized surge pricing, where fares automatically rise during peak demand times to balance driver supply and passenger demand [29]. Beyond these applications, DP has extended to entertainment ticketing, retail, food delivery, and electricity markets, demonstrating its versatility across sectors [24]. This adoption reflects the growing availability of real-time data, advancements in computing technology, and increased acceptance of variable pricing among consumers accustomed to price fluctuations in digital marketplaces.

Among the industries covered in this review, e-commerce and digital platforms occupy a distinctive position. Unlike sectors where price changes involve regulatory review, physical repricing costs, or fixed contractual terms, e-commerce platforms can adjust prices continuously at near-zero marginal cost, using data drawn directly from individual browsing, purchase, and competitor-monitoring signals [8,12,28]. These characteristics make e-commerce/digital platforms a useful reference context for comparing AI-based dynamic pricing applications across industries, including reinforcement learning-based demand response in energy markets and surge pricing in ridesharing.

2.2. Artificial Intelligence in DP

AI-based dynamic pricing uses AI to adjust prices in real time in response to changing market conditions and customer behavior [30]. Unlike traditional methods based on predefined rules and manual adjustment, AI-based systems use machine learning (ML), neural networks (NN), and deep learning (DL) to process large datasets and automate pricing decisions [31]. These systems can analyze multiple variables simultaneously, including purchase histories, competitor prices, inventory levels, seasonal patterns, demand changes, weather, and local events. A key capability of AI-based dynamic pricing is continuous learning from new data, which can support faster price adjustment than manual processes [32,33]. This technology has transformed DP from a reactive strategy into a proactive revenue optimization tool that can predict future market conditions and adjust prices accordingly.

AI-based DP operates through several interconnected components that jointly support pricing decisions. At its core, data collection systems gather information from various sources, such as transaction histories, website analytics, competitor tracking tools, social media sentiment, and external market data [34]. ML algorithms use regression for demand forecasting, classification for customer segmentation, and RL for sequential decisions in uncertain settings. Deep reinforcement learning (DRL) methods, including DQN, PPO, and SAC, model dynamic pricing as a Markov decision process in which pricing policies are learned through repeated interaction with the environment [35]. NN within these systems estimate Q-values or policy gradients that represent the expected long-term revenue for dif-

ferent pricing actions, continuously updating their parameters based on observed outcomes and rewards [36]. Trained models can then generate real-time pricing recommendations and be updated as new data become available.

Recent research has examined increasingly sophisticated AI-based DP methods across multiple industries. DRL has been used effectively on major e-commerce platforms such as Alibaba, where experiments involving thousands of products produced measurable gains in revenue conversion relative to manual pricing [31,37]. Advanced neural network architectures, including convolutional neural networks for pattern recognition and multi-head attention mechanisms for handling complex temporal dependencies, have enhanced pricing systems' ability to capture non-linear relationships among pricing factors [35]. The integration of continuous price optimization, rather than discrete pricing tiers, has enabled more precise alignment with customer willingness-to-pay and real-time market conditions. Recent research has also concentrated on solving the cold-start problem for new products through transfer learning and pre-training on historical data. It also involves developing algorithms that can manage price competition in oligopolistic markets without causing algorithmic collusion [38,39]. Furthermore, hybrid approaches that combine multiple AI methods have also been investigated.

Understanding AI-based DP as a holistic system is essential for several critical reasons that impact both academic research and business practice. First, evaluating components in isolation may overlook how data quality, algorithm selection, training methodology, and deployment strategy jointly influence system performance [40]. Second, market-level effects may include price volatility, changes in competitive dynamics, and algorithmic collusion risks [35]. For firms, implementation requires attention to algorithm selection, methodological limitations, ethical considerations, and governance arrangements [34]. Finally, understanding the gaps between theoretical capabilities and practical constraints is crucial for advancing both research and real-world applications that balance profit optimization with fairness, transparency, and long-term customer relationships.

3. Methodology and Data

This study uses a structured mixed-method bibliometric approach to map the field, explore methodological changes, and identify themes in AI-based DP research. Bibliometric analysis provides a systematic way to identify patterns in scientific knowledge creation, such as publication paths, collaboration networks, and thematic area [41,42]. Guided by established best practices in bibliometric and systematic review research [43–45], the methodological framework (Figure 1) comprises descriptive analysis, bibliometric mapping, and qualitative thematic interpretation. Literature was retrieved from Scopus and filtered through the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) procedure to ensure rigor and transparency in data selection. The analytical process brings together quantitative methods such as co-citation analysis, keyword co-occurrence, and cluster detection, along with thematic analysis, to help understand emerging research areas, methodological trends, and how these are applied across different industries. To support these analyses, the study employs CiteSpace 6.4.R2 Advanced for burst detection and co-occurrence structures [46], VOSviewer 1.6.20 for visualizing collaboration and keyword networks [47], and Python 3.9.12 for the evolution of AI techniques across different industries and visualization [48]. This triangulated design supports reproducibility and provides a comprehensive understanding of how AI techniques are shaping contemporary DP research.

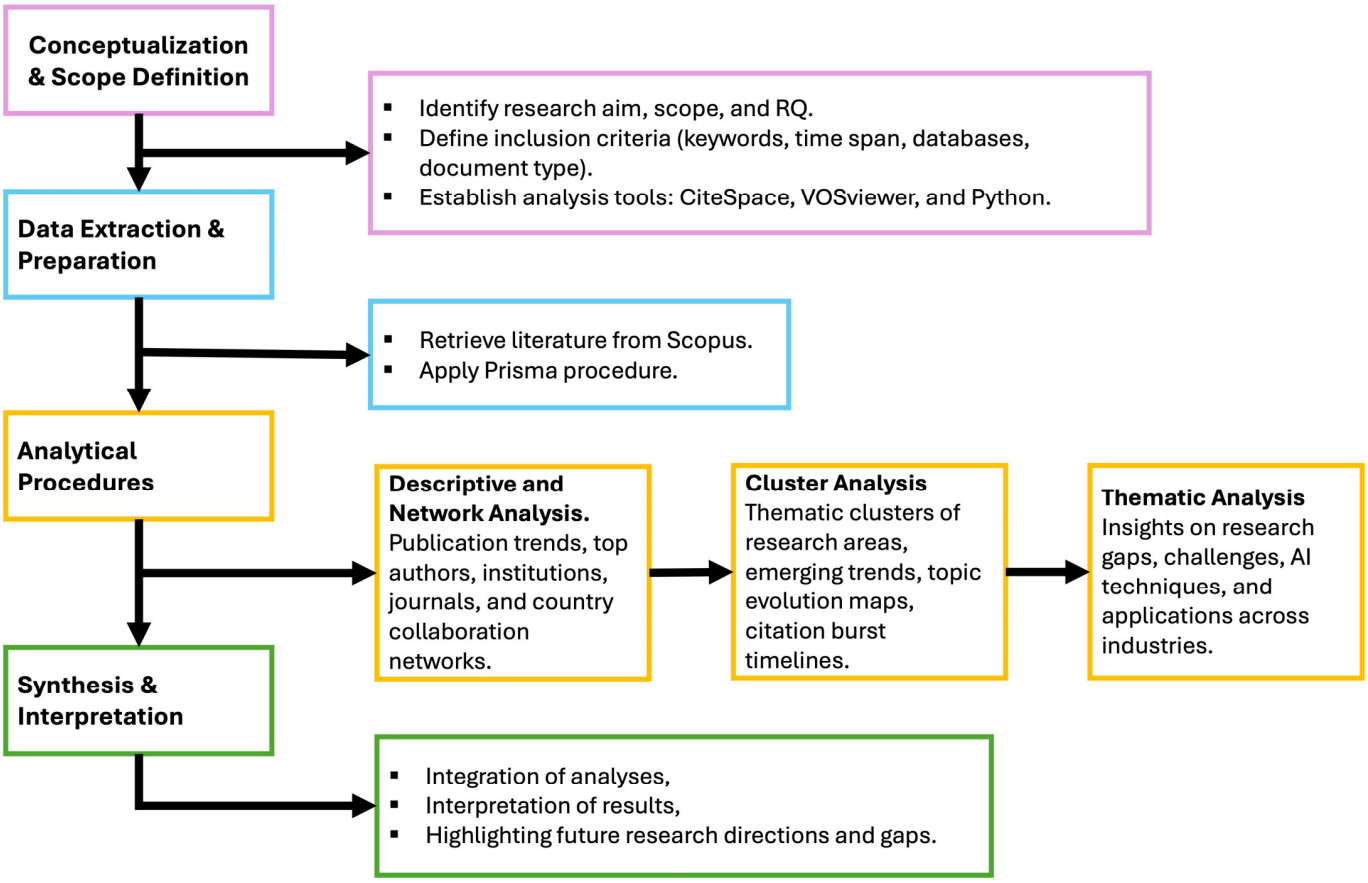


Figure 1. Methodological Approach.

3.1. Data Collection

The literature dataset was sourced from Scopus, selected for its broad, well-documented coverage of peer-reviewed research in AI, ML, operations research, and applied business domains. Scopus is widely used in bibliometric and scientometric studies and is particularly strong in indexing AI and engineering-oriented journals and conference proceedings, making it well suited for analyzing AI-based dynamic pricing research. This review was conducted and reported in accordance with the PRISMA guidelines where applicable to systematic and bibliometric reviews. A PRISMA flow diagram is provided in Figure 2 to document the identification, screening, eligibility assessment, and inclusion process. No review protocol was registered as the study was designed as a bibliometric and thematic review based on bibliographic metadata rather than as an intervention-based systematic review.

The search strategy was developed using an iterative, literature-informed approach. Initial keywords were derived from prior reviews and bibliometric studies on DP and AI-enabled decision systems and refined through pilot searches to balance coverage and specificity. Controlled vocabulary and free-text terms related to AI, ML, and DP were combined using Boolean operators, the complete search string is reported below. The bibliographic search was conducted in Scopus on 15 August 2025 using the TITLE-ABS-KEY field, which retrieves records based on titles, abstracts, and keywords. The final search query was: TITLE-ABS-KEY ((“dynamic pricing” OR “price optimization” OR “pricing strategy” OR “revenue management”) AND (“artificial intelligence” OR “AI” OR “machine learning” OR “ML” OR “deep learning” OR “DL” OR “reinforcement learning” OR “RL” OR “neural networks” OR “NN” OR “predictive analytics” OR “time-series forecasting” OR “demand prediction” OR “forecasting models”)). No wildcard or truncation operators were applied.

The following Scopus filters were applied: language, English; subject areas, Computer Science; Engineering; Business, Management and Accounting; Mathematics; Decision Sciences; Economics, Econometrics and Finance; Energy; and Social Sciences; publication years, 2005–2025. No document-type restriction was applied.

The initial Scopus search returned 1590 records. After removing 179 records through English-language and relevant Scopus category filtering, 1411 records remained for screening. These records were screened by title, abstract, and keywords to confirm relevance to AI-based dynamic pricing; records were excluded if they fell outside the scope of AI-based DP, were duplicates, contained incomplete bibliographic records, or were otherwise unsuitable for bibliometric analysis. Relevance and eligibility screening excluded a further 110 records, yielding a final curated dataset of 1301 records. The final dataset was exported in CSV and TXT formats with full bibliographic metadata for analysis using CiteSpace, VOSviewer, and Python.

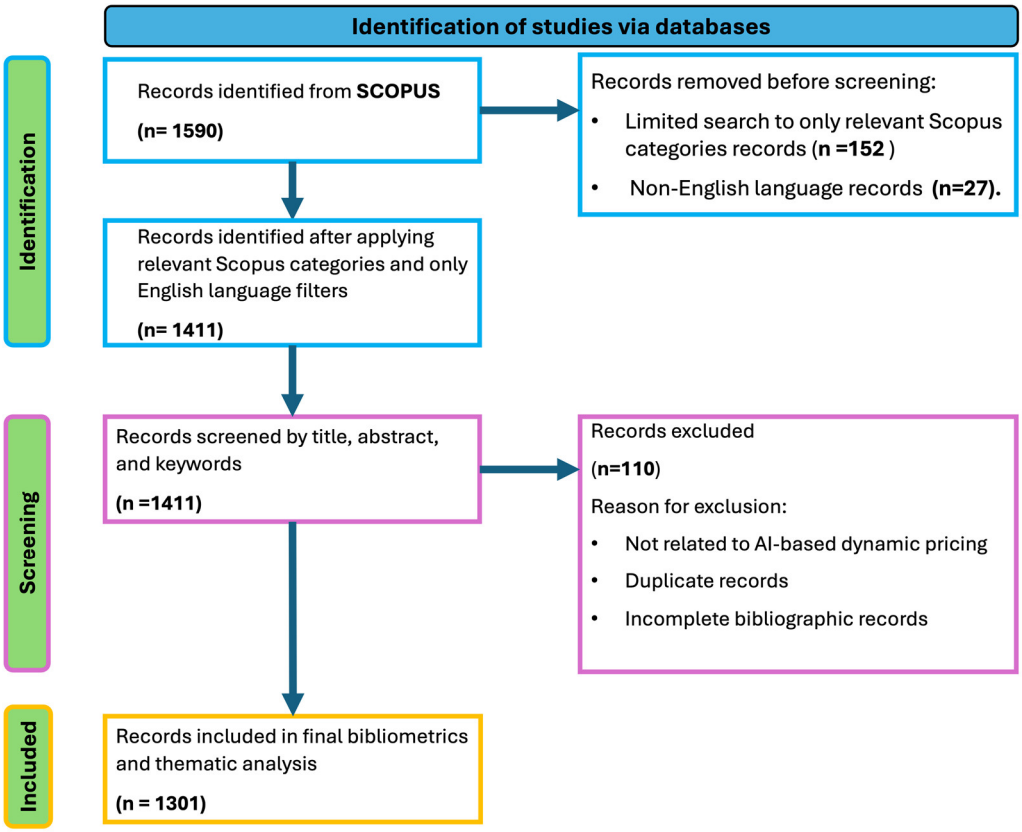


Figure 2. PRISMA flowchart.

3.2. Descriptive Analysis

In this stage, descriptive analyses are used to summarize the main features of the dataset and provide a broad understanding of the AI-based DP research landscape, addressing RQ1. By examining publication trends, citation patterns, leading authors, journals, institutions, and contributing countries, this analysis highlights how scholarly attention to the field has evolved and which actors have played key roles in its development. These insights give a foundational understanding of the scope, growth, and distribution of research activity, helping to identify influential contributions and emerging areas of interest. This descriptive overview serves as a starting point for the next analytical steps, guiding a deeper exploration of the field's structure, themes, and intellectual landscape progression.

3.3. Bibliometric and Thematic Analysis

The bibliometric analysis explores the intellectual framework and thematic development of AI-based DP research, addressing RQ2 and RQ3. This phase focuses on identifying conceptual connections, influential works, and emerging research trends through co-citation and keyword co-occurrence analysis [4,47,48]. Co-citation patterns reveal theoretical connections, while keyword co-occurrence mapping identifies thematic clusters that signal the field's dominant topics and evolving interests [49,50]. Temporal analyses, including citation-burst detection and keyword evolution timelines, capture shifts in scholarly attention and highlight emerging paradigms such as the transition from rule-based pricing to machine-learning- and reinforcement-learning-based strategies. These analyses were conducted using CiteSpace for cluster detection and burst-term identification [46] and VOSviewer for visualizing co-occurrence networks and thematic density maps [47].

VOSviewer macOS version 1.6.20 was used to construct and visualize the networks. Full counting was applied so that each relationship received equal weight. Association-strength normalization was used, and total link strength represented the cumulative strength of an item's connections. The minimum inclusion thresholds were 30 documents for countries, 5 documents for institutions, and 5 occurrences for keywords. Items meeting these thresholds were ranked by total link strength, and the most strongly connected items were retained for visualization.

The standard VOSviewer layout and clustering settings were retained, including a clustering resolution of 1.00, a minimum cluster size of one item, and attraction and repulsion values of 2 and 1, respectively. Advanced parameters were not manually modified. Before analysis, keywords were standardized by merging singular and plural forms, spelling variants, abbreviations, and equivalent terms, including "machine learning" and "ML," "deep learning" and "DL," and "reinforcement learning" and "RL." Both author and indexed keywords were considered where available. In the resulting maps, nodes represent items, links represent relationships, node size reflects the selected weight, and node color indicates cluster membership.

CiteSpace 6.4.R2 Advanced for Mac was used to complement the VOSviewer analysis through keyword clustering, timeline visualization, citation-burst detection, and analysis of the field's intellectual base. The analysis covered 2005–2025 using one-year time slices, with keywords selected as the node type for co-occurrence, clustering, timeline, and burst analyses, and cited references used for intellectual-base analyses. Standard CiteSpace settings were retained, including the default g-index-based selection procedure for identifying influential items within each annual slice, with no manual modification of advanced selection parameters. Pathfinder scaling and pruning of individual time-slice networks were applied to reduce redundant links and improve map interpretability. Clusters were labelled using the log-likelihood ratio method, while citation bursts were identified through CiteSpace's standard burst-detection procedure. Cluster quality was evaluated using modularity Q and silhouette values, where higher modularity indicates clearer separation among clusters and higher silhouette values indicate greater internal consistency.

To address RQ4, a complementary thematic coding procedure was applied to the 1301 records using information from titles, abstracts, author keywords, and indexed keywords. Four dimensions were examined: Technique, Application, Industry, and AI Model. An automated keyword-matching process was first implemented in Python using a coding dictionary that included recurring terms, abbreviations, spelling variants, and domain-specific expressions. The resulting candidate classifications were then manually reviewed to remove false positives, interpret ambiguous terms, and add missing codes when the study focus was clear. Records could receive multiple Technique, Application, or AI Model codes, while each record was assigned to its principal industry context based on the stated

research objective and application setting. The validated results were analyzed in Python through publication frequencies, temporal comparisons, cross-tabulations, heatmaps, and Sankey diagrams.

4. Results

The final dataset comprises 1301 Scopus-indexed publications issued between January 2005 and August 2025 (Table 1). The records were drawn from 391 sources and involved 2844 authors, with an average of 6.75 co-authors per publication. The dataset contains 3039 author keywords and 5859 indexed keywords. Publications received an average of 12.56 citations per document, and annual publication output grew by 20.92%.

Table 1. Characteristics of the data.

Description	Results
Timespan	January 2005–August 2025
Sources (e.g., journals, books)	391
Documents	1301
Average citations per document	12.56
Authors	2844
co-Authors per Document	6.75
Author's Keywords (DE)	3039
Keywords Plus (ID)	5859
Annual Growth Rate %	20.92

The dataset comprises 564 articles, 545 conference papers, 86 book chapters, 68 conference reviews, 24 review papers, 10 books, 2 short surveys, and a small number of other Scopus-indexed records. In aggregated terms, journal articles and reviews account for 588 records, conference papers and conference reviews for 613, and books and book chapters for 96. No document-type weighting was applied because AI-based DP research spans disciplines in which both journal and conference publications are relevant. The leading Scopus subject areas are Computer Science (859 records), Engineering (518), Business, Management and Accounting (319), Mathematics (301), Decision Sciences (260), Economics, Econometrics and Finance (152), Energy (139), and Social Sciences (108). Because Scopus permits multiple subject-area assignments, these counts overlap and are not mutually exclusive.

4.1. Overview of AI-Based DP Research

Figure 3 shows the annual publication distribution of AI-based dynamic pricing research across industries from 2005 to 2025. Early publications were concentrated in Airline/Aviation, Tourism & Hotel/Hospitality, and Transport/Logistics. Publication output increased after approximately 2015 and rose more sharply after 2020. During the later period, publication activity also expanded in E-commerce/Digital Platforms, Retail, Manufacturing/Supply Chain, Finance, EV Charging, and Healthcare/Medical. E-commerce/Digital Platforms accounts for 269 publications, representing approximately 20.7% of the 1301 records classified for Figure 3. Section 5 discusses this category in relation to automated repricing, real-time data use, and behavioral analytics.

Figure 4 offers an overview of the international landscape of AI-based DP research. Figure 4A presents the country-level collaboration network, while Table 2 reports publication counts, citations, and total link strength (TLS) for the ten most productive countries. China records the highest publication count and TLS, followed by the United States and India in publication output. The United States has the highest citation count. The network

also includes collaborative links among several European countries. TLS represents the cumulative strength of a country's collaboration links within the network.

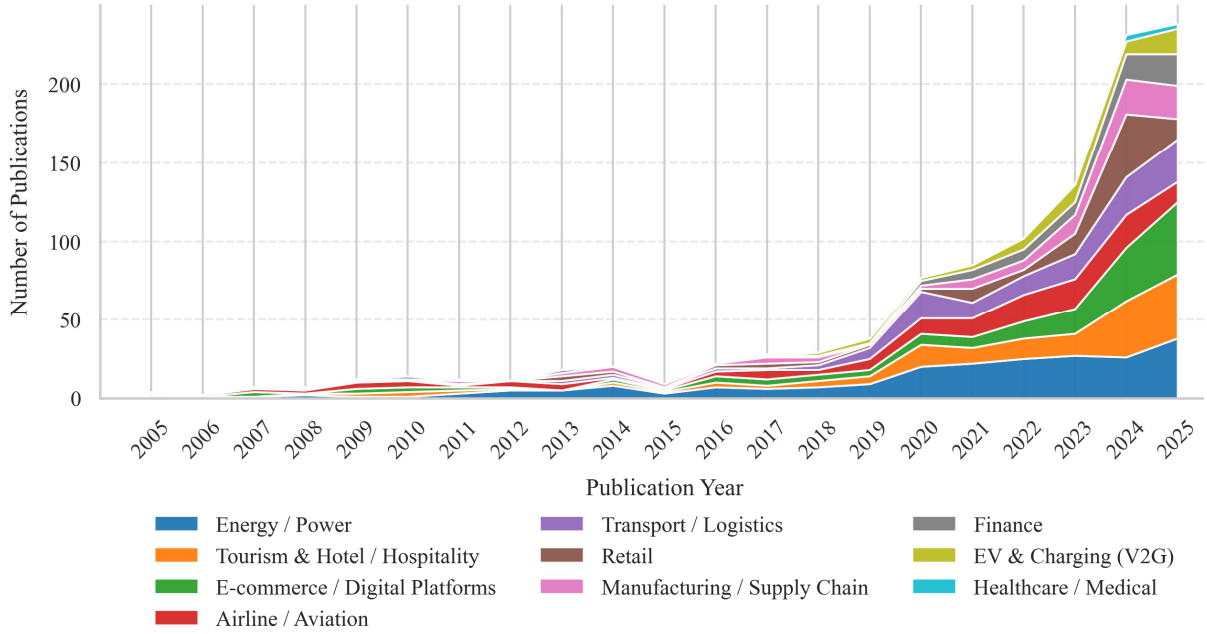


Figure 3. Publication trends of AI-based DP research across industries over time.

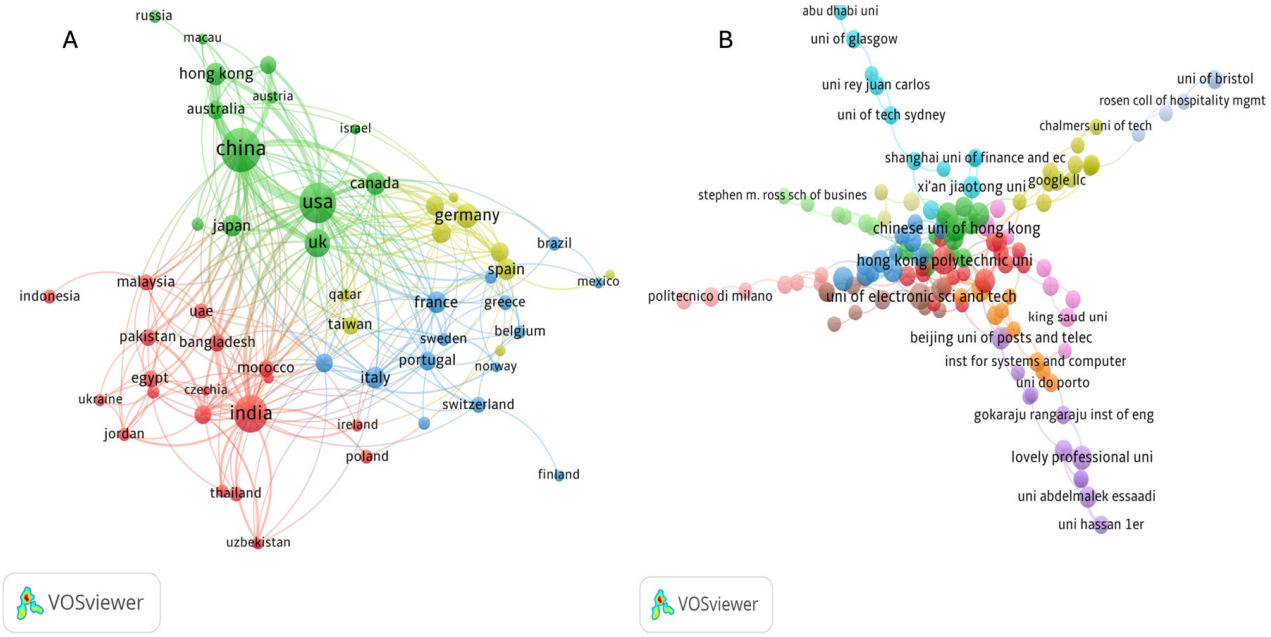


Figure 4. (**A**) Country collaboration network, and (**B**) institutional collaboration network.

Figure 4B and Table 3 summarize institutional publication and collaboration patterns. The Hong Kong Polytechnic University has the highest publication, and citation counts among the listed institutions. The Chinese University of Hong Kong and the University of Electronic Science and Technology of China follow in publication count, while Southeast University, Tsinghua University, and Shanghai Jiao Tong University record comparatively high citation or TLS values. Most of the ten leading institutions are in China or Hong Kong.

Table 2. Top 10 countries by publication count, citations, and TLS.

Rank	Country	Counts	Citations	TLS
1	China	352	4636	164
2	USA	248	6532	152
3	India	204	1120	76
4	UK	76	1903	63
5	Germany	51	313	29
6	Hong Kong	40	1508	49
7	Canada	39	365	32
8	Japan	35	797	18
9	Spain	33	394	16
10	France	31	1130	26

Table 3. Top 10 institutions by publication count, citations, and TLS.

Rank	Organization	Counts	Citations	TLS
1	The Hong Kong Polytechnic Uni.	17	991	17
2	The Chinese Uni. of Hong Kong	14	314	15
3	Uni. of Electronic Science and Technology of China	14	208	12
4	Southeast Uni.	12	626	10
5	Tsinghua Uni.	12	295	11
6	Guangdong Uni. of Technology	10	227	11
7	Lovely Professional Uni.	10	81	6
8	Wuhan Uni. of Technology	10	20	1
9	Shanghai Jiao Tong Uni.	9	345	12
10	Sun Yat-sen Uni.	9	79	8

4.2. Research Trends and Thematic Clusters in AI-Based DP

Figure 5 presents complementary keyword analyses of the thematic structure and development of AI-based DP research. The VOSviewer co-occurrence network in Figure 5A identifies frequently associated keywords related to forecasting, reinforcement learning, optimization, market simulation, and industry-specific pricing applications. The CiteSpace analysis in Figure 5C organizes related keywords into thematic clusters, providing a complementary representation of the field's principal research areas. Figure 5B identifies the strongest keyword bursts and the periods during which terms such as reinforcement learning, smart grid, DL, pricing strategy, and EV charging received increased attention. The keyword timeline in Figure 5D displays the temporal distribution of the thematic clusters. Earlier keywords are associated with conventional pricing and econometric modeling, whereas later periods show greater prominence of ML, reinforcement learning, multi-agent systems, and real-time applications in energy and digital markets. Together, the analyses identify the field's principal thematic areas and changes in their prominence over time. Section 4.3 further examines the distribution of AI techniques across industries.

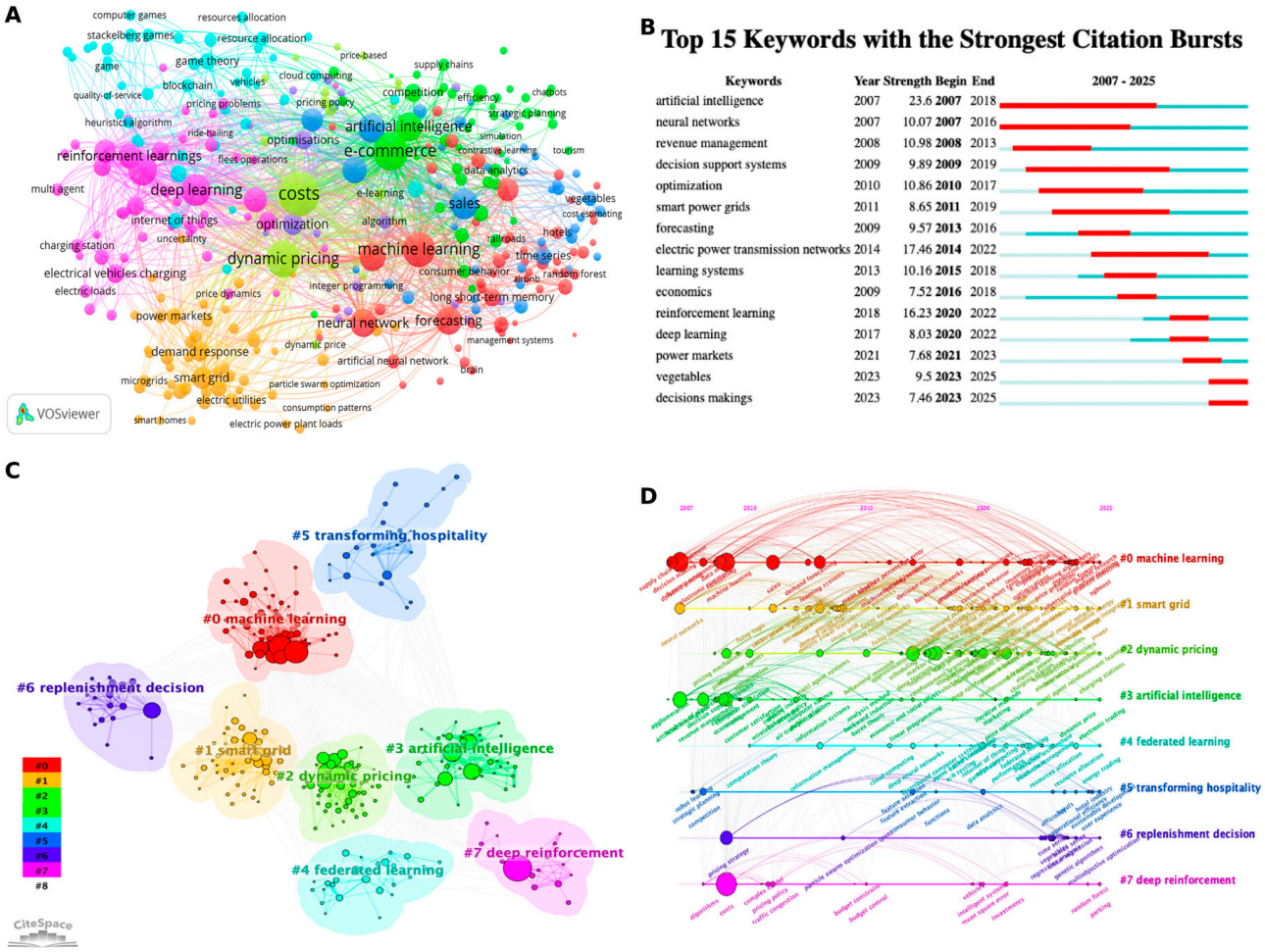


Figure 5. Keyword analyses of AI-based DP research: (**A**) keyword co-occurrence network generated using VOSviewer; (**B**) 15 keywords with the strongest bursts; (**C**) keyword cluster analysis generated using CiteSpace; and (**D**) keyword-cluster timeline.

4.3. Evolution of AI Techniques and Industry Applications in DP

Figure 6 shows the temporal distribution of AI-based DP publications across industries, revealing differences in the timing and growth of research activity. Earlier publications were concentrated in established revenue-management settings, whereas later research covers a broader range of industries. Airline/Aviation and Tourism & Hotel/Hospitality maintain comparatively stable publication patterns over time. Publication activity in E-commerce/Digital Platforms, Energy/Power, and Retail increases more sharply in the later years of the study period. EV Charging (V2G), Finance, and Healthcare/Medical appear later in the publication record and increase toward the end of the study period. Overall, Figure 6 shows that the timing and growth of AI-based DP research differ across industries. Established revenue-management domains remain represented throughout the period, while e-commerce/digital platforms and several newer application areas account for an increasing share of later publications.

Figure 7 shows the annual frequency of AI-model categories identified in DP publications from 2005 to 2025. Statistical and econometric methods are more prominent in the earlier years, while heuristic and simulation-based approaches also appear during this period. After 2015, the frequency of publications coded under ML increases. The strongest increase occurs after 2020, particularly for reinforcement learning and hybrid-model categories. DL-related publications also increase during this period. Overall, the

figure indicates a broadening of the methodological profile of AI-based DP research, with statistical and econometric approaches remaining present alongside increasing use of ML, DL, reinforcement learning, and hybrid models.

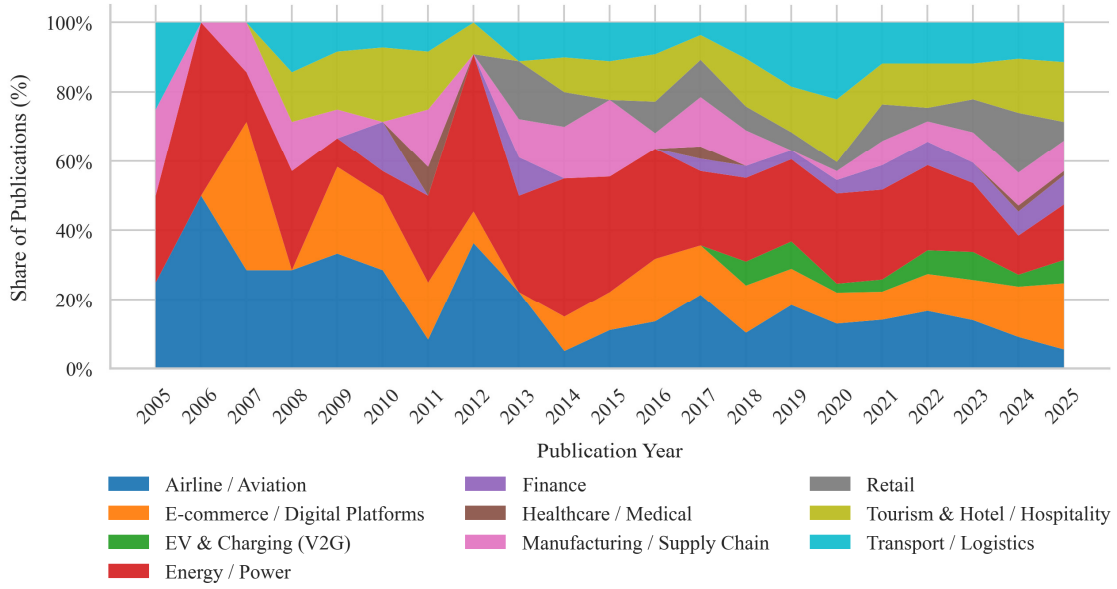


Figure 6. Evolution of AI-based DP across industries.

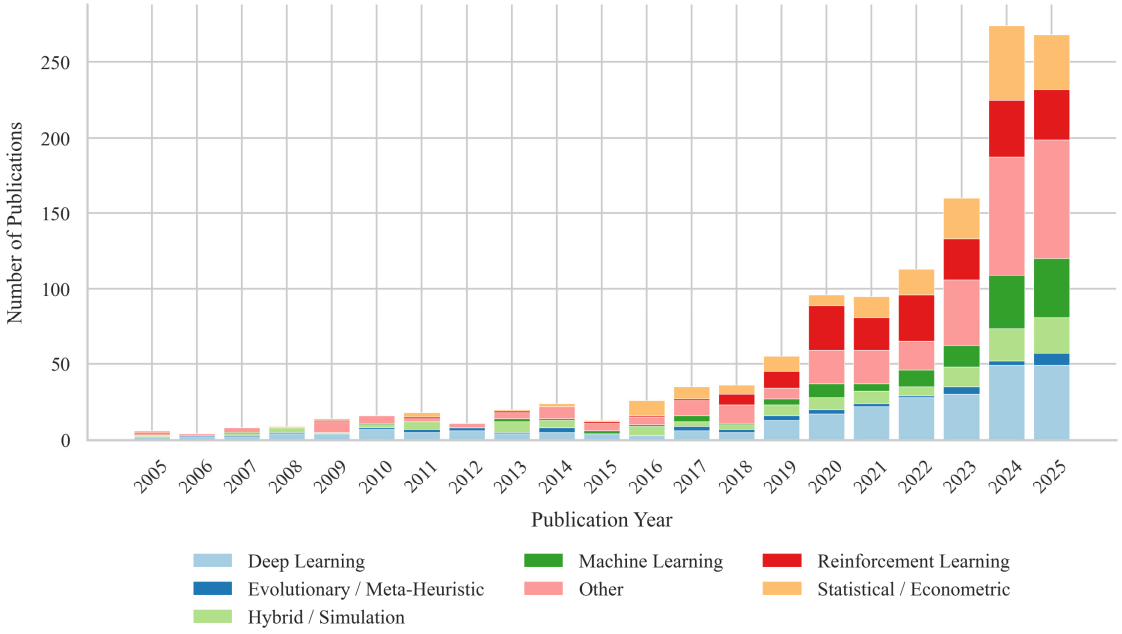


Figure 7. Temporal trends of AI model categories.

Figure 8 presents the frequency of coded AI techniques across principal industry categories. Because individual records could receive multiple technique codes, the heatmap reports cumulative technique occurrences rather than unique document counts. Each record was assigned to one principal industry, consistent with the coding procedure described in Section 3.3. The categories were derived from title, abstract, and keyword coding. Neural networks, reinforcement learning, and Monte Carlo or simulation-based methods emerge as the most widely used approaches, although their prominence varies substantially across sectors.

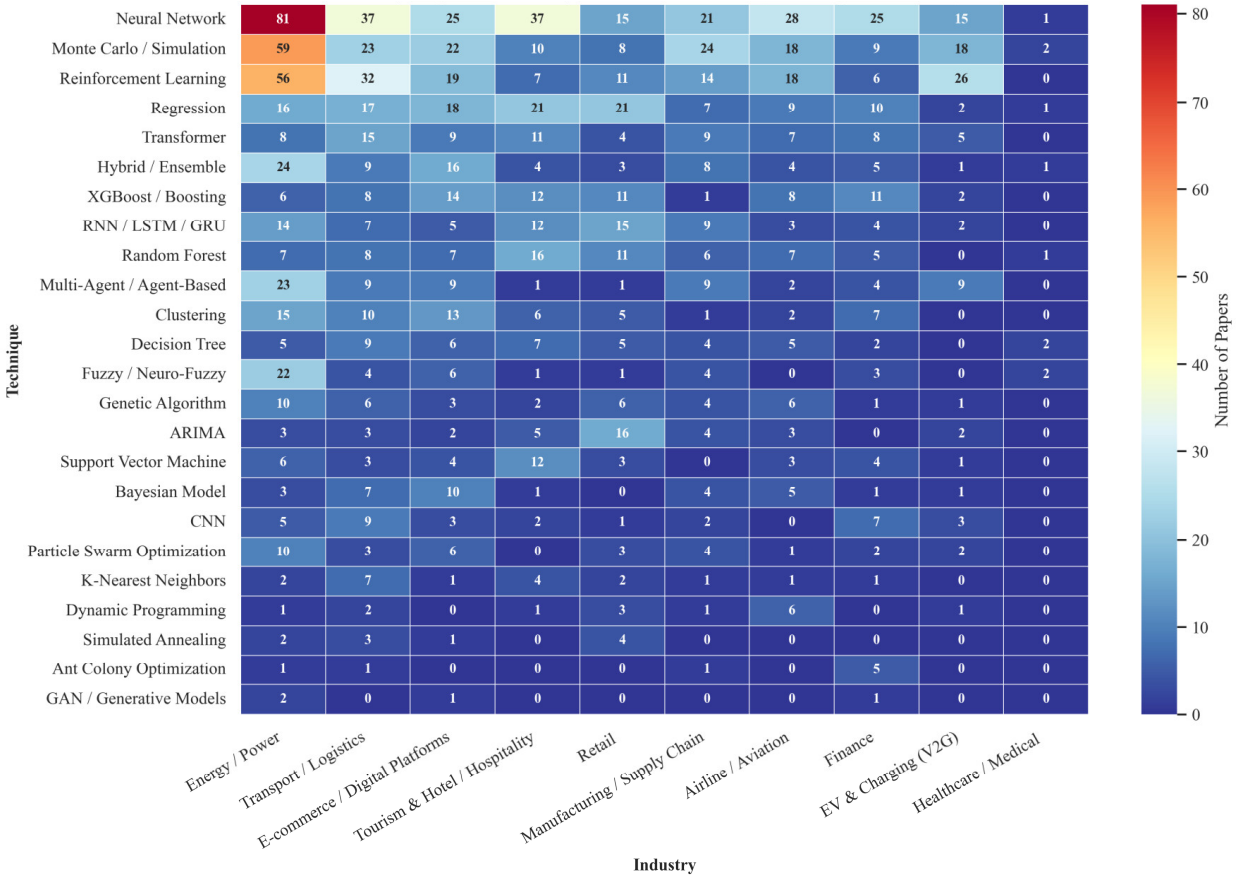


Figure 8. Mapping of AI techniques across industries.

Energy/Power publications frequently include reinforcement learning, metaheuristic optimization, and hybrid or simulation-based methods. E-commerce/Digital Platforms and Retail show comparatively frequent associations with neural networks, gradient boosting, and transformer-based models. These categories are also linked in the coding results to demand forecasting and customer-behavior prediction. Manufacturing/Supply Chain publications include a comparatively mixed distribution of heuristic optimization, Bayesian models, and decision-tree methods. EV Charging (V2G) and Healthcare/Medical display a narrower distribution of coded techniques than several larger industry categories. Overall, the heatmap shows that the distribution of AI techniques differs across industry categories. These associations describe patterns in the reviewed literature and do not establish the comparative effectiveness or operational adoption of the techniques.

Figure 9 visualizes the coded relationships among AI techniques, DP applications, and principal industry categories. Neural networks, reinforcement learning, and metaheuristic or simulation-based approaches are connected to multiple application categories, including forecasting, price optimization, market design, and sequential decision-making. Reinforcement learning is frequently connected to real-time or adaptive pricing applications, particularly in Energy/Power, EV Charging (V2G), and Transport/Logistics. Neural networks and gradient-boosting methods are associated with forecasting and predictive-modeling applications, particularly in E-commerce/Digital Platforms, Retail, and Manufacturing/Supply Chain. Metaheuristic and hybrid-optimization techniques are linked to scheduling and optimization applications, especially in Manufacturing/Supply Chain and Energy/Power. Healthcare/Medical and Finance exhibit narrower technique–application pathways in the coded dataset. Overall, the Sankey diagram summarizes recurring associations among techniques, pricing applications, and industries. These relationships provide a basis for the

cluster-level interpretation presented in Section 5 but should not be interpreted as evidence of causal selection or comparative model performance.

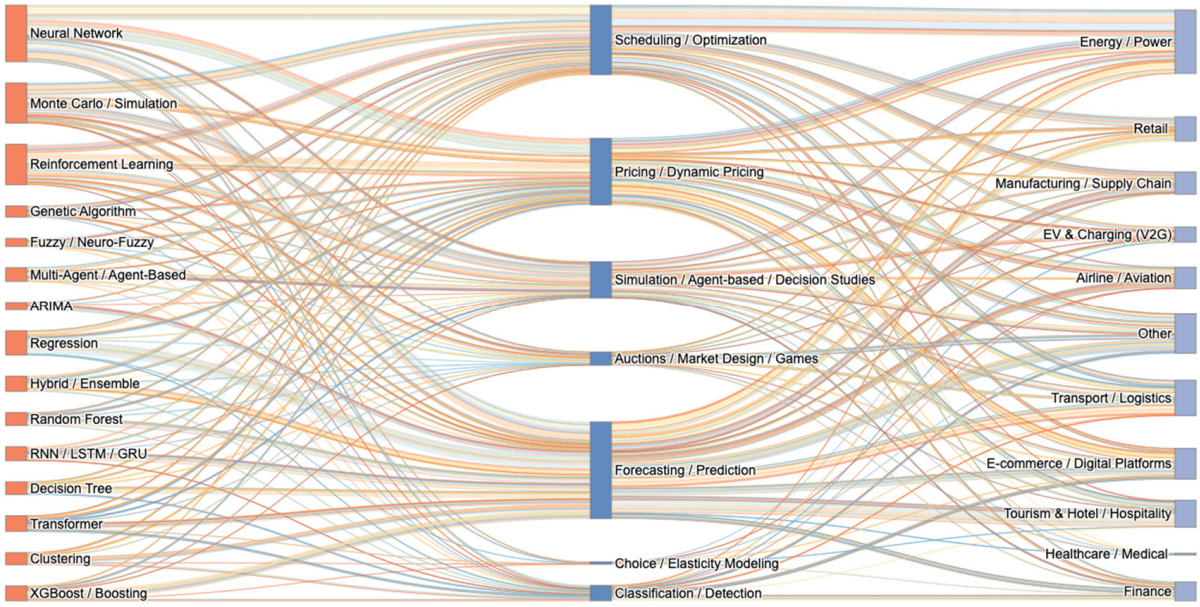


Figure 9. Sankey diagram showing the flow from AI techniques to pricing applications and industry domains.

5. Discussion

Taken together, the bibliometric and thematic results show that AI-based DP research has expanded across methodological and industry contexts, with e-commerce/digital platforms representing a prominent application domain. The following subsections interpret the identified thematic clusters, methodological patterns, and cross-industry relationships. Because the analysis is based on bibliometric records and abstract-level thematic coding, the discussion addresses patterns in the research literature rather than the implementation or effectiveness of AI-based pricing systems.

5.1. Research Hotspots and Thematic Clusters

The keyword analysis identified eight clusters, labeled Cluster #0 through Cluster #7 according to CiteSpace's numbering convention. The cluster boundaries were generated from keyword co-occurrence rather than predetermined by the authors, and cluster size reflects keyword occurrences rather than unique publication counts. Because individual publications may contain keywords associated with multiple clusters, the clusters are interpreted as thematic orientations rather than mutually exclusive bodies of the literature.

Cluster #0 (ML) groups studies on ML, reinforcement learning, and demand forecasting. Its topics include integrated forecasting and multiproduct price optimization in online fashion retail [51], high-dimensional feature learning for personalized pricing [52], experimental and bandit-based online pricing under limited information [53], and spatiotemporal pricing in ride-sourcing and mobility platforms [54].

Cluster #1 (smart grid) represents an application-oriented energy and smart-grid cluster within AI-based DP. A primary focus is on accurate load forecasting as a key step for price-responsive tariffs, often using deep neural networks to improve short-term demand prediction [55]. Building on these forecasts, later work uses DRL to automate real-time electricity pricing and manage unpredictable demand [56], extends DP to EV charging and microgrids [57], and designs optimal tariffs that consider consumer elasticity and responsiveness to prices. This cluster suggests that forecasting, DL, and multi-agent decision

systems are increasingly important research directions in AI-based pricing for modern electricity systems.

Cluster #2 (DP) represents a core conceptual and pricing-strategy cluster focused on the development and refinement of DP models across traditional revenue-management industries. Much of this research combines demand forecasting with price optimization, using econometric, ML, and hybrid models to adjust prices based on real-time market conditions. Foundational studies include the analytics-driven pricing systems in fashion retail [51] and clearance optimization in fast-fashion environments [58]. In aviation and transportation, dynamic fare optimization is widely studied through models that balance demand fluctuations, load factors, and competitive pressures [59].

Cluster #3 (AI for traditional revenue management) covers established revenue-management settings, including hospitality, aviation, retail, and online marketplaces. Recent studies show that AI-enhanced occupancy forecasting and NN-based rate adjustment can outperform manual hotel pricing rules [60]. In retail and online marketplaces, data-driven repricing methods leverage observed market data to estimate demand, anticipate competitor responses, and update prices in real time [61,62]. Complementing these operational models, simulation platforms such as Price Wars allow firms to test automated strategies under realistic competitive dynamics [63].

Cluster #4 (federated learning) links federated learning, edge computing, blockchain, and incentive-based pricing. Studies in this cluster aim to enable privacy preserving and decentralized intelligence in markets where raw data cannot be centrally collected. One line of work develops incentive-compatible payment schemes for federated learning participants, rewarding high-quality local model updates through contract- or game-theoretic pricing schemes [64,65]. Another approach combines blockchain and smart contracts to secure and audit DP and data-trading transactions in IoT and energy settings [66,67]. Additional studies pair multi-agent RL with edge or vehicular computing to jointly manage resource allocation and pricing [68]. This cluster indicates growing scholarly interest in decentralized AI architectures for pricing contexts involving privacy, transparency, and autonomous learning.

Cluster #5 (transforming hospitality) focuses on DP, demand forecasting, and risk management within the hospitality and tourism industries. A key area develops ML and DL models for short-term hotel demand forecasting, achieving significant accuracy improvements over traditional methods [69,70]. Another focus addresses booking cancellations and no-shows through interpretable prediction models, supporting more reliable overbooking and capacity planning [71,72]. These predictive tools are increasingly integrated into DP strategies that consider seasonality, competition, and host differences, as seen in research on Airbnb pricing and perceived market power [73]. Overall, this cluster indicates that advanced analytics is increasingly studied to support more flexible, data-driven hospitality revenue management.

Cluster #6 (replenishment decision) emphasizes the joint optimization of pricing and replenishment, especially in grocery, fresh-food, and supermarket contexts. Studies combine ARIMA, LSTM, and hybrid deep models with metaheuristic optimization techniques [74]. The aim is to convert demand forecasts into real-time price and stock suggestions that cut waste in perishable goods while keeping profits high [34]. Outside of fresh food, related research applies ML to retail price recommendations and promotion planning in e-commerce and supermarket settings.

Cluster #7 (DRL) groups studies that apply DRL to support fully autonomous pricing in complex and changing environments. Here, pricing is modeled explicitly as a sequential control problem under uncertainty, using methods such as DQN, PPO, SAC, and multi-agent actor–critic algorithms. Applications include toll pricing on express lanes, where

DRL models simultaneously boost revenue and reduce congestion [75], EV charging and grid coordination [76], and DP for perishable inventory [77]. This group highlights a research direction in which learning agents are increasingly examined as alternatives or complements to human-designed pricing rules that adapt to feedback, nonlinear dynamics, and strategic interactions over time.

For synthesis, the eight clusters can be organized into three broad orientations: methodological clusters comprising ML, federated learning, and DRL; application-oriented clusters covering smart grids, hospitality, and replenishment decisions; and the conceptual DP cluster linking pricing strategy and revenue management. This organization shows the coexistence of general AI methods and domain-specific pricing problems within the literature. This organization shows the coexistence of general AI methods and domain-specific pricing problems within the literature. Section 5.2 examines the implications of these patterns for e-commerce and digital platforms.

5.2. E-Commerce and Digital Platform Insights

Within the reviewed literature, e-commerce/digital-platform studies combine real-time market data, frequent price adjustment, customer-level information, and automated seller interaction. These characteristics are most visible in Cluster #0, Cluster #3 and Cluster #6. Table 4 summarizes the associated e-commerce themes and their relationships with other industry contexts.

Cluster #3 includes data-driven repricing studies that estimate demand, monitor market conditions, and account for competitor responses [61,62], as well as simulation environments for evaluating pricing strategies under competition [63]. Related studies examine reinforcement-learning-based competition [32], self-learning agents in recommerce markets [38], and spatiotemporal pricing in ride-sourcing [54]. Together, these studies connect e-commerce research on seller-level interaction with multi-agent and spatial coordination problems in other platform-mediated markets. They also identify algorithmic collusion as a relevant governance concern [35].

Cluster #0 includes online-pricing studies that use high-dimensional customer and transaction information to estimate heterogeneous willingness to pay [52] and learn pricing policies under incomplete demand information through experimentation and bandit-based methods [53]. This transaction-level granularity is a defining feature of electronic commerce, where browsing, purchase, inventory, and competitive signals can all be linked to a single pricing decision. Comparable hospitality and energy studies in the reviewed literature tend to operate at more aggregated levels, such as host, property, household, or load-profile segments [73], suggesting these sectors may adopt similar demand-learning techniques as privacy protections and data access permit.

Forecasting is linked to pricing in hospitality [69,70], energy [55], and e-commerce [34,52]. E-commerce studies additionally connect demand forecasts with replenishment, inventory control, and promotion decisions [34,51]. This comparison distinguishes product-level pricing and inventory decisions in e-commerce from the capacity- and system-demand settings examined in other industries.

Energy-pricing research addresses tariff fairness, consumer welfare, and regulatory oversight [22], while e-commerce research on algorithmic collusion identifies competition and accountability concerns arising from interactions among autonomous pricing agents [35]. The comparison identifies platform-level oversight and seller-level algorithmic interaction as related but distinct governance topics.

As summarized in Table 4, these themes position e-commerce as a reference domain for examining the interaction of AI, customer data, rapid repricing, seller competition, and platform governance. The cross-industry analysis identifies recurring methodological and

governance concerns while also showing that differences in data, market structure, and regulation limit direct generalization across sectors.

Table 4. Representative e-commerce and digital-platform studies and their cross-industry insights.

E-Commerce and Digital-Platform Theme	Representative Studies	Main Insight for E-Commerce Research	Cross-Industry Relevance
Real-time repricing and platform competition	Schlosser and Boissier [61]; Schlosser et al. [62]; Fisher, Gallino, and Li [63]	Online marketplaces use observed market data to estimate demand, monitor competitors, and update prices dynamically; simulation environments support evaluation of automated repricing strategies before deployment.	Ride-sourcing research [54] contributes spatial and multi-agent coordination models, while e-commerce contributes a detailed treatment of seller-level strategic interaction in rapidly changing markets.
Seller-level strategic interaction	Kastius and Schlosser [32]; Schlosser and Kastius [38]	Self-learning agents model competition among sellers operating within the same marketplace, including recommerce settings where pricing decisions are linked to acquisition, resale, and inventory conditions.	Supports research on algorithmic collusion [35] and informs multi-agent pricing models emerging in mobility, energy, and other platform-based markets.
Customer behavior tracking and personalization	Ban and Keskin [52]; Misra, Schwartz, and Abernethy [53]	Customer and transaction information supports heterogeneous willingness-to-pay estimation, sequential learning, and adaptive pricing under incomplete demand information.	Offers granular demand-learning approaches that may be adapted to hospitality, mobility, and energy where privacy, customer acceptance, and data availability permit.
Forecasting and operational integration	Ferreira, Lee, and Simchi-Levi [51]; Yavuz and Kaya [34]	Demand forecasts relate to pricing, inventory, replenishment, and promotional decisions in online retail and marketplace settings.	Hospitality forecasting [69,70] and energy load forecasting [55] offer complementary approaches for incorporating capacity, scheduling, and system-level constraints.
Fairness, transparency, and platform governance	Deng, Schiffer, and Bichler [35]	Automated pricing raises concerns related to collusion, accountability, consumer welfare, and platform oversight—concerns that intensify when prices change frequently and customer-level data inform them.	Energy-pricing research offers more established fairness and regulatory frameworks, while e-commerce contributes evidence on seller- and transaction-level algorithmic interaction.

5.3. Evolution of AI-Based DP

Figure 10 synthesizes the temporal patterns identified in the bibliometric and thematic analyses of AI-based DP research. Earlier research was concentrated in aviation, hospitality, and retail and emphasized structured heuristics, econometric demand models, and established revenue-management methods. Later publications expanded toward algorithmic pricing in retail, logistics, ticketing, and e-commerce/digital platforms. Publications from the later period show greater attention to ML-based forecasting and optimization, while those after 2020 increasingly address DL, reinforcement learning, multi-agent systems, and

simulation-based pricing. Later research also covers mobility, EV charging, smart-grid management, and digital marketplaces. These patterns describe changes in the research literature and do not indicate that newer methods have replaced earlier approaches or that industries have adopted them uniformly. Section 5.4 develops future research opportunities from these temporal and cross-industry patterns.

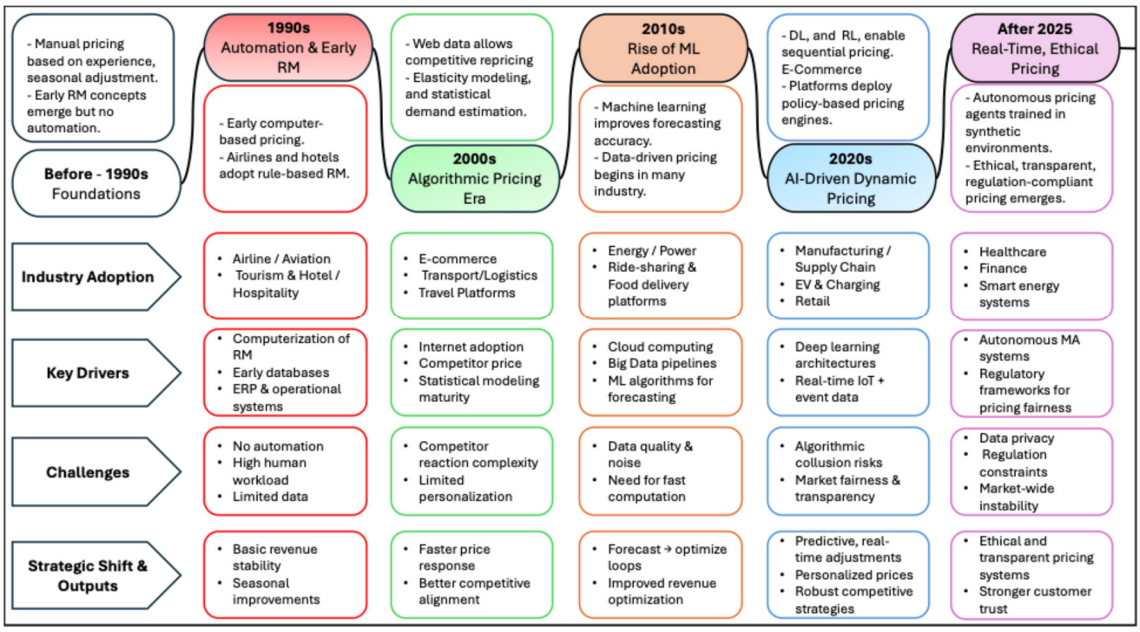


Figure 10. Evolution of AI-Based DP and its implications.

5.4. Future Research Direction

The following research directions are derived from bibliometric patterns, thematic clusters, and abstract-level coding and therefore require validation through systematic content analysis, empirical studies, and industry-specific research. Figure 11 summarizes differences in the AI methods associated with industry categories in the reviewed literature. Established revenue-management domains are frequently linked to forecasting and econometric models, whereas later-emerging application areas show stronger associations with reinforcement learning, simulation, and multi-agent methods.

A first direction concerns the relationship between AI methods and industry context. The reviewed literature associate hospitality primarily with forecasting, aviation with parametric demand models, retail with supervised ML, and energy with reinforcement learning. Future studies should test whether methods developed in one sector remain effective under different demand structures, competitive conditions, data environments, and regulatory constraints. Relevant comparisons include reinforcement-learning models across mobility and e-commerce, forecasting models across hospitality and EV charging, and causal demand-estimation methods across retail and energy.

A second direction concerns data access and comparative evaluation. Detailed pricing data are often unavailable because of privacy, regulation, or commercial confidentiality, including in e-commerce and digital-platform settings. Shared simulation environments, realistic synthetic datasets, standardized evaluation protocols, and appropriately anonymized industry data would support more transparent comparison of AI-based pricing methods across studies and sectors.

A third direction involves interactions among autonomous pricing agents. Future studies should examine the stability, equilibrium, and welfare effects of multi-agent pricing, including the potential for unintended collusion, strategic responses, or price am-

plification. These questions are particularly relevant to online marketplaces and other platform-mediated environments in which several sellers or service providers adjust prices simultaneously.

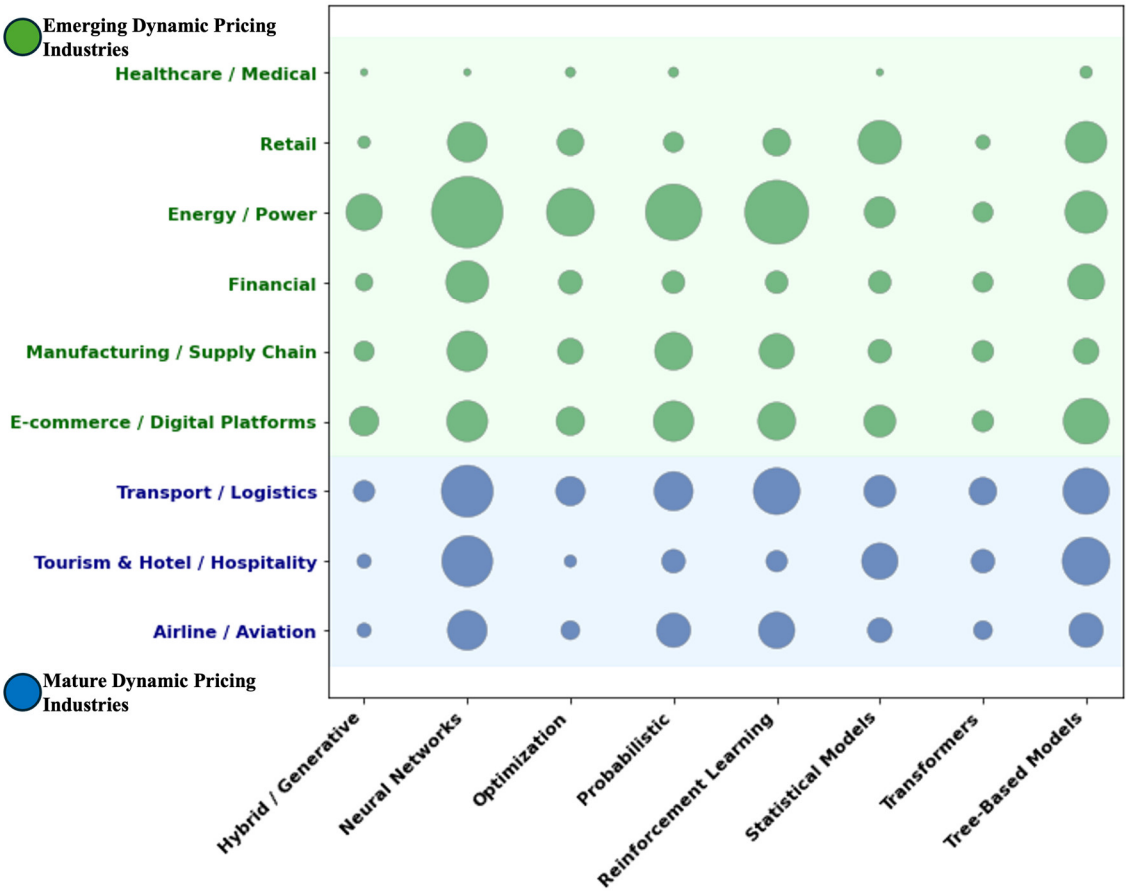


Figure 11. Patterns of model adoption across traditional and emerging DP industries. Circle size represents the number of coded occurrences of each model category within the corresponding industry.

A fourth direction concerns explainability, fairness, and governance. Research should evaluate how pricing models affect different customer groups, how personalized prices are perceived, and whether model decisions can be audited by managers, platforms, and regulators. Relevant topics include explainable pricing policies, fairness-aware objectives, human oversight, and evaluation frameworks that consider revenue alongside consumer welfare and other context-specific outcomes.

A fifth direction is to extend research beyond large, data-rich organizations and frequently studied industries. Future studies could examine AI-based DP in SMEs and in less represented contexts such as healthcare, education, and B2B markets. Such work should consider data and computational constraints, organizational capabilities, customer trust, and the behavioral effects of frequent or personalized price changes.

E-commerce/digital platforms provide a useful setting for cross-industry comparison because they combine automated execution, behavioral data, and rapid competitive interaction. Future research should empirically test whether governance approaches from regulated sectors, such as tariff-fairness mechanisms in energy [22], can be adapted to online marketplaces. Conversely, competitive repricing [61–63] and personalized demand-learning methods [52,53] developed in e-commerce could be evaluated in mobility, hospitality, or energy settings. Such studies should not assume that models or governance

practices will perform similarly across different market structures, data conditions, and regulatory environments.

Together, these directions emphasize empirical comparison, improved data access, multi-agent market behavior, governance, and context-sensitive implementation. For e-commerce research, the central challenge is to evaluate AI-based pricing not only as a prediction or optimization problem but also as a platform-level system involving sellers, customers, competitors, and governance arrangements.

5.5. Contributions and Limitations

5.5.1. Theoretical Contributions

This study contributes to the literature by integrating bibliometric analysis, science mapping, temporal analysis, and thematic coding to examine the structure of AI-based DP research. The eight keyword clusters provide a structured representation of the field's principal methodological and application-oriented themes, including forecasting, ML, reinforcement learning, federated learning, revenue management, smart grids, hospitality, and replenishment decisions.

A second contribution is the connection of keyword clusters with coded AI techniques, pricing applications, and principal industry categories. This combined analysis extends studies that examine general DP trends, individual industries, or broad publication indicators by showing how methodological and application themes are distributed across the reviewed literature. These results describe research patterns and do not establish industry adoption, implementation effectiveness, or comparative model performance.

A third contribution concerns the positioning of e-commerce/digital platforms as the study's principal comparative lens. The reviewed e-commerce literature links real-time repricing, customer-level data, seller competition, demand forecasting, personalization, and platform governance. Comparing these themes with energy, mobility, hospitality, retail, and other pricing contexts identifies both recurring research concerns and sector-specific constraints. This positioning distinguishes the study from e-commerce-focused reviews [4,12] and broader cross-industry reviews [3,17] that do not use e-commerce/digital platforms as an explicit reference domain.

5.5.2. Practical Implications

The study also provides several practical insights for industries adopting or expanding AI-based pricing systems. The findings provide a literature-based reference for organizations considering AI-enabled dynamic pricing. The shift from static, spreadsheet-based pricing to DL and reinforcement learning, shown in Figure 10, reflects how research attention has changed as data availability and computational capabilities have expanded. This pattern may help managers identify the types of methods commonly examined at different levels of analytical and operational complexity. However, it does not establish when an organization should adopt a particular approach or whether that approach will improve performance in a specific setting.

The industry-specific patterns shown in Figure 11 may help practitioners consider which techniques are more commonly studied in similar operational environments. Forecasting, clustering, and price-elasticity modelling appear prominently in research on retail, e-commerce, hospitality, and other established revenue-management environments. Reinforcement learning and multi-agent systems are more often associated with settings characterized by sequential decisions, real-time changes, and decentralized interactions. These associations may provide an initial reference for evaluating possible analytical approaches, but their practical suitability depends on data quality, market structure, organizational capabilities, regulatory constraints, and empirical testing within the intended application.

Another practical implication is the need for more robust data-sharing mechanisms across industries. Many techniques identified in the clusters require richer, higher-frequency, or more granular datasets than are usually available to researchers or smaller firms. Greater access to anonymized and research appropriate datasets may therefore support further evaluation of these methods. At the same time, the growing importance of fairness, transparency, and regulatory compliance across pricing contexts suggests that organizations should consider interpretability, customer effects, and governance when assessing automated pricing systems, particularly in sectors involving essential services such as mobility and energy.

As pricing systems become more automated and complex, building managerial trust and integrating decision support are essential. Even accurate recommendations may go unused if practitioners do not understand or trust the underlying logic. Managerial trust and workflow integration may influence whether AI-based pricing recommendations are used. Scenario explanations, human oversight, and clear communication of model limitations are therefore relevant implementation considerations. These implications should be interpreted as patterns and considerations derived from the literature rather than as evidence that any individual AI method is operationally or financially superior.

5.5.3. Limitations

Although this review provides a broad overview of AI-based DP, several limitations should be acknowledged. First, thematic coding based on titles, abstracts, author keywords, and indexed keywords cannot capture the full methodological details, implementation conditions, or empirical performance reported in each publication. Second, reliance on Scopus may exclude relevant publications indexed in other databases, as well as industry reports and other nonacademic sources. Third, keyword clustering depends on authors' terminology and may produce fluid or overlapping thematic boundaries, particularly in rapidly developing areas such as energy markets, EV charging, and multi-agent reinforcement learning. Fourth, the review covers published academic research and excludes proprietary pricing systems that are not publicly documented. Future reviews could address these limitations through multiple databases, full-text and expert validation of thematic classifications, and comparative evaluation using shared or synthetic datasets. Finally, the e-commerce-specific interpretation in Section 5.2 is derived from the cross-industry clusters, coded records, and cited studies rather than from a separate e-commerce-only subsample. It should therefore be interpreted as a focused synthesis of the existing results rather than as an additional empirical analysis.

6. Conclusions

This study examined 1301 Scopus-indexed publications from 2005 to 2025 using bibliometric analysis, science mapping, and thematic coding. The analysis identified eight thematic clusters spanning forecasting, ML, reinforcement learning, federated learning, revenue management, smart grids, hospitality, and replenishment decisions. Temporal and cross-industry patterns show greater methodological diversity in later publications and differences in the AI techniques associated with industry categories.

The review also identifies gaps concerning data access, comparative evaluation, multi-agent market behavior, and governance. E-commerce/digital platforms provide the study's principal comparative lens because the reviewed literature connects customer-level data, rapid repricing, seller competition, forecasting, personalization, and platform governance within a common market setting. Cross-industry comparison can support future empirical testing of whether pricing methods and governance approaches remain valid under different market structures, data conditions, and regulatory requirements. The study therefore

contributes a structured account of how AI methods, pricing applications, and industry contexts are represented and connected in the literature, while its findings should be interpreted as research patterns rather than evidence of implementation effectiveness.

Author Contributions: Conceptualization, D.O.; methodology, D.O.; software, D.O.; validation, D.O., M.J. and S.W.; formal analysis, D.O.; investigation, D.O.; data curation, D.O.; writing—original draft preparation, D.O.; writing—review and editing, D.O., M.J. and S.W.; visualization, D.O.; supervision, M.J. and S.W.; project administration, M.J. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The datasets analyzed in this study were derived from the Scopus database and processed by the authors. Due to Scopus licensing restrictions, the underlying bibliographic data are not publicly available. The curated data and analysis scripts are available from the corresponding author upon reasonable request, subject to applicable licensing conditions.

Acknowledgments: The authors are grateful to the editor and anonymous reviewers for their valuable feedback on an earlier draft of this manuscript. The authors used ChatGPT (OpenAI, version 5.2) for language editing and revision support. All substantive intellectual contributions, analysis, and final manuscript decisions were made exclusively by the authors.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
DP	Dynamic Pricing
ML	Machine Learning
DL	Deep Learning
RL	Reinforcement Learning
DRL	Deep Reinforcement Learning
DQN	Deep Q-Network
PPO	Proximal Policy Optimization
SAC	Soft Actor-Critic
EV	Electric Vehicle
V2G	Vehicle-to-Grid
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RQ	Research Question
TLS	Total Link Strength
ARIMA	Auto Regressive Integrated Moving Average
LSTM	Long Short-Term Memory

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