Artificial Intelligence and Dynamic Pricing: A Systematic Literature Review

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Abstract

With dynamic pricing becoming more widespread across various industries, artificial intelligence has made it even more sophisticated and widespread. The authors conducted a systematic literature review and analyzed a dataset of 95 peer-reviewed articles from international journals selected in Web of Science and Scopus to better understand artificial intelligence's impact on dynamic pricing. The authors identified four clusters related to financial modeling, market dynamics, commodity markets, and behavior and decision-making. They also found that China has overtaken the US in the number of published articles. They identified the themes of market simulation investment, crude oil commodity dependence, and behavior traders' prices. A systematic literature review is essential to understand the impact of artificial intelligence on dynamic pricing and its implications for businesses, consumers, and society.

Keywords: artificial intelligence, dynamic pricing, systematic literature review

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1 Introduction

Dynamic pricing has become a common strategy across various industries, from airlines and gas stations to retail and entertainment. Dynamic pricing has become even more sophisticated and widespread with the increasing use of artificial intelligence. Recent media articles comment on the phenomenon. For instance, The Wall Street Journal (2022) reports that prices change online and offline. The Conversation (2022) investigates the potential of smart meters and dynamic pricing to reduce pollution and save money. The Guardian (2022) states that "40% of brands that use artificial intelligence to personalize customer experience have adjusted pricing (...) Amazon reprices millions of items as frequently as every few minutes."

The increasing use of artificial intelligence in dynamic pricing has garnered attention from both the media and academic communities. Misunderstanding the impact of artificial intelligence on dynamic pricing can result in missed business opportunities and reduced competitiveness in the market (Hobler, 2022). Indeed, outdated pricing methods favor the risk of missing out on cost-saving and revenue-generating possibilities (Fan et al., 2022). On the other hand, understanding artificial intelligence's impact on dynamic pricing enables organizations make data-driven strategies to optimize pricing strategies. Optimal dynamic prices increase revenue and profitability and keep pace with changing market conditions and consumer behavior (den Boer, 2015). Nevertheless, the actual link between artificial intelligence and dynamic pricing, though widely commented on, still needs to be debated. So far, practitioners and academics need to reach a consensus. Consequently, a systematic literature review becomes essential to understand the impact of artificial intelligence on dynamic pricing and its implications for businesses, consumers, and society.

To further explore the influence of artificial intelligence on dynamic pricing, this article conducts a systematic literature review, providing a comprehensive overview of the theoretical basis and existing gaps in research (Aria and Cuccurullo, 2017; Di Vaio et al., 2020). It gives a comprehensive view of the concepts, including their theoretical basis and existing gaps in research. We have identified three main premises: using multiple data sources, incorporating market information, and deploying sophisticated algorithms (Jungell-Michelsson and Heikkurinen, 2022). After considering different sources (Web of Science, Scopus, ScienceDirect, for instance), our dataset contains 95 peer-reviewed articles from international journals, selected from 368 articles. We used the R package Bibliometrix to analyze the dataset. These premises provide a solid footing for artificial intelligence and dynamic pricing. Several studies evaluate the interaction between artificial intelligence and dynamic pricing and their effect on different economic players and scales. Nevertheless, further integrated research is necessary to understand artificial intelligence's potential impact on dynamic pricing, which we discuss in this article.

Dynamic pricing, the practice of adjusting prices in response to changes in supply and demand, has become increasingly prevalent in many industries due to advancements in technology and the availability of data. Literature reviews show that dynamic pricing has been extensively studied in specific fields, such as transportation, electricity, the sharing economy, and revenue management. Without being field-specific, literature reviews also provide regular state-of-the-art information on dynamic pricing.

Technology and data availability advancements have led to the increasing prevalence of dynamic pricing in many industries. In specific fields, such as transportation, electricity, sharing economy, and revenue management, dynamic pricing has been extensively studied, with researchers exploring various pricing strategies and their impact on economic players and scales. In transportation, research has focused on applying dynamic pricing techniques in Intelligent Transportation Systems in smart cities (Saharan et al., 2020). Another study analyzed revenue management in passenger transportation (Ammirato et al., 2020). In the sharing economy, a systematic literature review was conducted to explore pricing strategies (Yang and Xia, 2021). Dutta and Mitra (2017) review the dynamic pricing schemes in electricity.

A more general overview of dynamic pricing was provided by Chenavaz et al. (2011), who reviewed dynamic pricing in management science. Den Boer (2015) analyzed the historical origins, current research, and new directions in dynamic pricing and learning. Neubert (2022), found that dynamic pricing has become a widely used strategy in various industries and business domains and has proven to be an effective tool for companies to improve their profitability and competitiveness.

Overall, these studies highlight the importance and prevalence of dynamic pricing in various industries and business domains. However, these literature reviews needed to integrate the artificial intelligence foundation of dynamic pricing.

In top to showing a growing (exponential) interest in artificial intelligence-based dynamic pricing by scholars and practitioners, our main contributions are the following:

- We find four clusters related to financial modeling, market dynamics, commodity markets, and behavior and decision-making. This contribution provides a better understanding of the current state of the field and the areas where there is a growing interest and potential for further research. The four clusters offer a valuable framework for organizing and categorizing future research.
- We highlight that China overtook the USA in terms of the number of published articles in 2020, while the USA still had the most citations. This contribution highlights that China is rapidly increasing its research production in this field. Also, American research remains highly valued in the academic community.
- We identify motor themes thanks to a thematic map. These themes are market simulation investment, crude oil commodity dependence, and behavior traders' prices. This contribution helps guide researchers' future work and ensures they are aligned with current trends and developments. It also provides a starting point for identifying gaps in the literature that need to be filled.

The article is organized as follows: Section 2 describes the methodology of our systematic literature review, explaining the data collection and the search phases. Section 3 presents the results based on the abstracts and keywords, the countries and affiliations, the journals and articles, the different clusters, and the thematic map. We discuss the literature around the main clusters and a thematic map in Section 4. We discuss the results, emphasizing the theoretical and practical implications, the research gaps, limitations, and conclusions in Section 5.

2 Method

Following the methodology of Tranfield et al. (2003) and Paul and Criado (2020), we propose a systematic literature review on artificial intelligence-based dynamic pricing. In accordance with the standard methodology of systematic literature reviews (Aria and Cuccurullo, 2017; Di Vaio et al., 2020; Sandelowski et al., 1997; Tranfield et al., 2003), and considering the early discussions on artificial intelligence driven dynamic pricing, our data analysis emphasizes field interpretation. This approach contrasts with other statistical and bibliometric analyses, which typically utilize a larger number of studies for statistical purposes without delving into detailed examination. Table 1 summarizes the main elements of the systematic literature review, adopting the method from Callahan (2014) 's 6W framework (see also Di Vaio et al. 2020).

2.1 Data collection

We systematically review the literature published up to May 2024, using the methods and techniques proposed by Tranfield et al. (2003) and Paul and Criado (2020). Pilot research on three easily accessible databases, namely Google scholar, Elsevier, and ScienceDirect, for "artificial intelligence" and "dynamic pricing" (without further restriction) gave 11.200, 9.652, and 689 results. In a nutshell, a lot has been

Table 1: Main elements about the systematic literature review

Who conducted the review?	The authors of the paper
When were the data collected?	May 2024
Where were the data collected?	Web of Science
hoW were the data found?	Sampling
What was found?	Final data set 95 articles
	Search word in title, abstract, and keywords
Which selection criteria?	Peer-reviewed article with pdf, English,
	"artificial intelligence" and "dynamic pricing"

Adapted from Callahan (2014)'s 6W framework

written on artificial intelligence-based dynamic pricing. The issue is spotting the relevant articles to provide a sound, systematic literature review. The search was not limited by time, but due to the evolving nature of the debate on artificial intelligence and dynamic pricing, the sample was collected in three phases. Figure 1 overviews the journey from the pilot search to the final data.

2.1.1 First search phase: Database selection

In the first step of our process, we began by selecting the database. Aria and Cuccurullo (2017) claims that Web of Science has better data quality than other databases. Following the more recent studies of Fink (2019) and Di Vaio et al. (2020), we also use Web of Science as the central database. This database is widely used in socio-economic disciplines and has content similar in size to Scopus (Hicks and Wang, 2011). Web of Science also benefits from a standard format and needs fewer data-cleaning treatments than Scopus (Zupic and Čater, 2015).

The selection of a suitable database is a crucial aspect of conducting a literature review, as it can significantly affect the results' quality. In our process, we began by selecting the database, and after careful consideration, we opted for Web of Science as the central database, following the recommendations of recent studies (Di Vaio et al., 2020; Fink, 2019). We also searched for missing relevant references in other databases, Scopus, Google Scholar, and ScienceDirect, as Jungell-Michelsson and Heikkurinen (2022); Massaro et al. (2016); Rashman et al. (2009). Despite these efforts, new publications were kept from the data through the two searches. Note that we also considered the databases Dimensions and PubMed, but they did not provide reliable results and were thus discarded.

2.1.2 Second search phase: Article selection

In the second step, we carefully selected the essential articles via content analysis, which involved thoroughly reading the abstracts. We specifically focused on identifying the relevance of each article to the issues addressed in our study.

After selecting the database in the first step of our process, we moved on to the second step of selecting relevant articles through content analysis. This step involved identifying articles that met specific criteria related to artificial intelligence and dynamic pricing, which we detail in this paragraph. For relevance, we selected the data on this criteria: peer-reviewed articles from an academic journals, in English, with mention of the concepts of "artificial intelligence" and "dynamic pricing" in the title, abstract, or keywords. The Keygen of our query is: "TITLE-ABS-KEY("ARTIFICIAL INTELLIGENCE") AND ("DYNAMIC PRICING") AND (LIMIT-TO(ECONOMICS OR MANAGEMENT OR BUSINESS))" First, we searched the Web of Science and Scopus with no field restriction and got 287 and 67 articles. We noted that most articles were irrelevant to our study, as they came from computer science or applied mathematics. Second, then restricting to the relevant fields (economics, management, and business), we got 81 (Web of Science)

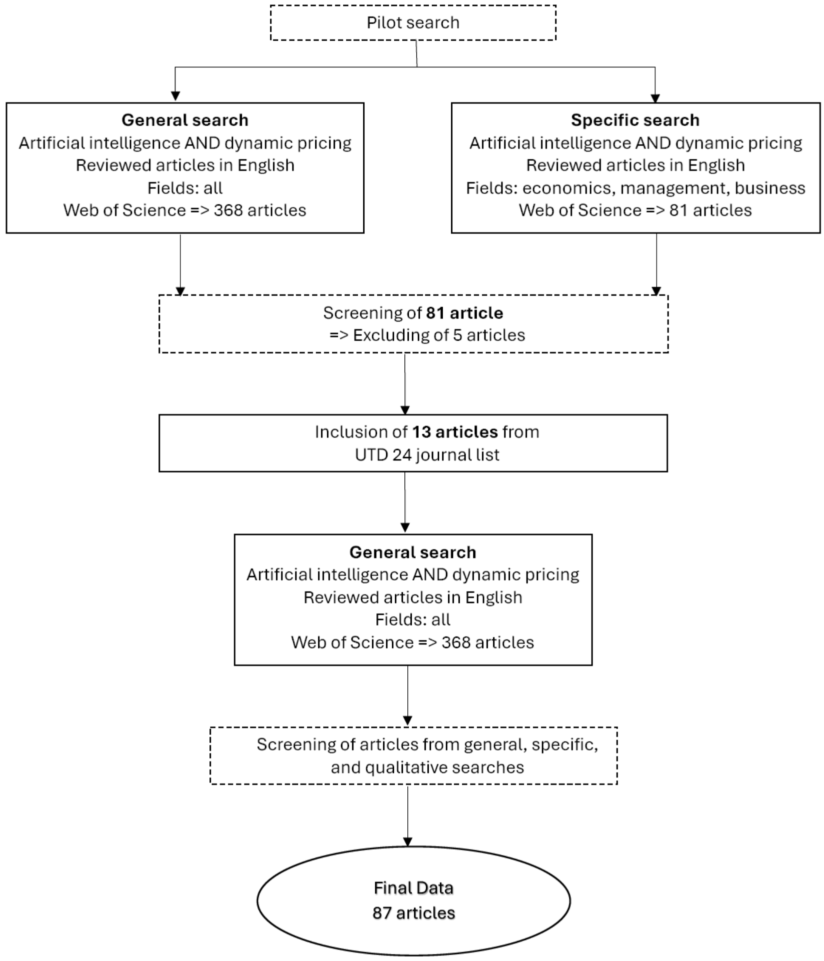

Figure 1: Overview of the search process and data selection

and 15 (Scopus) articles, for which the pdf was available. The final list of 81 articles from the Web of Science included 15 articles from Scopus.

2.1.3 Third search phase: Data organization

The content analysis allowed us to organize the data consistently and make it replicable. Each author worked independently to analyze the connection of each document to the topics of our investigation and then compared their results. This individual and comparative approach increased the reliability of the research (Di Vaio et al., 2020). Because of missing data or superficial links with our study, we excluded 5 articles, providing a final list of 74 articles.

After obtaining a list of articles that met the inclusion criteria, the next step was to conduct a content analysis to ensure the consistency of the data. This process involved independent analysis by each author, followed by comparison and consultation with experts in the dynamic pricing field to confirm that all essential publications were included. Experts in the dynamic pricing field were consulted to ensure that any essential publications meeting the data collection criteria were not missed. Several colleagues of the co-authors' teams specialized in dynamic pricing were consulted among the experts. They did not provide specific pointers in the literature to add. However, one of the experts, an anonymous reviewer, asked for the addition of relevant articles from UTD 24 journals. We could add 21 recent references. The purpose of this phase was to add publications not found in the database searches to the final data set. The final dataset consists then of 74+21=95 articles.

2.2 Data analysis

We analyzed the final dataset of 95 articles with the statistical language R and the library Bibliometrix (Aria and Cuccurullo, 2017). (Note that VOS Viewer is also an interesting software for data analysis Ali et al. 2023; Rahman et al. 2023.)

3 Results

For a comprehensive understanding, this section presents the result in the following order: bibliometric elements, abstract and keywords, countries and affiliations, and journals and articles. This section also organizes our discussion around the clusters emerging from our systematic literature review. Eventually, it uses a thematic map to guide our discussion of the key themes. Appendix A offers additional elements for completeness.

3.1 Bibliometric elements

The articles selected underwent bibliometric analysis to statistically and graphically analyze the research and emphasize the spatial and temporal elements of the insights. Bibliometric analysis enables a reproducible systematic literature review (Aria and Cuccurullo, 2017, pp. 959–960), ensuring reliable results in synthesis of scientific information on a topic, avoiding the risk of disregarding previous works.

After selecting the relevant articles, we conducted a bibliometric analysis to statistically and graphically analyze the research and emphasize the spatial and temporal elements of the results. Table 2 provides the primary data analyzed in the systematic literature review. The analysis spans 1999 to 2024 and includes 95 articles, 85 of which are regular and 2 are reviews. The annual growth rate of the analyzed literature is 0%. The average age of the documents is 6.84 years, and the average number of citations per document is 24.7. The total number of references cited in the analyzed literature is 4261, with 367 unique keywords and 248 authors. Of the 248 authors, 14 are authors of single-authored documents; there are 15 single-authored documents. In average, the number of co-authors per article is 2.98, and 27.59% of the co-author relationships are international.

Table 2: Main data information as generated via Bibliometrix Aria and Cuccurullo (2017)

Timespan	1999:2024
Articles	95
Regular articles	85
Reviews	2
Annual growth rate %	0
Document average age	6.8
Average citations per article	24.7
References	4261
Keywords	367
Authors	248
Authors of single-authored article	14
Single-authored article	15
Co-authors per article	3
International co-authorships %	27.6

3.2 Abstracts and keywords

The bibliometric analysis enabled us to construct a conceptual diagram illustrating the keywords correlation (Aria and Cuccurullo, 2017). Figure 2 presents the keywords organized by color, enhancing the readability of the concepts and their connections (Liu, 2004). The colors denote the frequency of keyword occurrences, with color correspondence indicating how often words appear together and highlighting the interconnected research questions. For example, the keywords 'dynamics' and 'commodity' are both colored blue, signifying their frequent co-occurrence. Similarly, the keywords 'model' and 'consumption' in orange, and 'prices' and 'crude-oil' in green, also tend to appear together.

The words "dynamics" and "model" are the largest, indicating they were the most commonly used terms in the abstracts, with 17 and 15 occurrences, respectively. The words "prices," "prediction," "volatility," and "behavior" also appear frequently, suggesting they are essential concepts in the study, with 9, 6, 6, and 6 occurrences, respectively.

Words such as "information," "market," "risk," "traders," and "uncertainty" suggest that the study may involve forecasting, analyzing market trends, or using technology to make decisions, each occurring 5 times. Terms like "algorithm," "competition," "demand," "design," "heterogeneous beliefs," "impact," "intelligence," "inventory," "liquidity," "management," "markets," "selection," "simulation," and "supply chain" highlight the study's focus on various aspects of financial operations and decision-making, each appearing 3 times.

One notes that the keywords "dynamics" and "financialization" and "model" and "genetic algorithms" have strong connections. The keywords "prices" and "investment," "prediction" and "markets," "volatility" and "neural network," and "behavior" and "optimization" also share connections.

The co-occurrence index in Figure 2 highlights the close relationship between artificial intelligence and dynamic pricing and how artificial intelligence represents a basis for dynamic pricing.

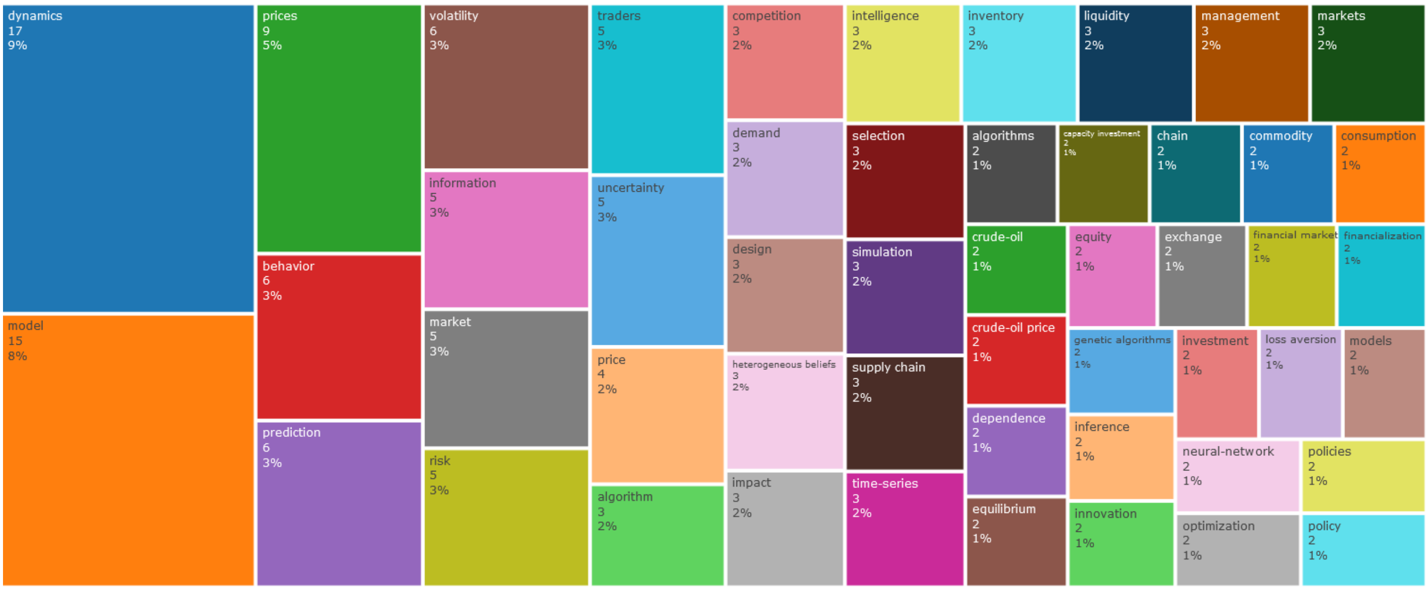

Figure 2: Word tree map in keywords: color measuring word occurrence as generated via Bibliometrix Aria and Cuccurullo (2017)

The frequency of specific keywords in academic articles from 1999 to 2024 reveals significant trends in the focus of research. The keywords "dynamics," "model," "prices," "prediction," "volatility," "behavior," "traders," "market," "price," and "risk" were analyzed in this dataset. From 1999 to 2008, the frequency of all keywords was relatively low, except for "dynamics," which had a frequency of 3 in 2008.

Over time, the frequency of all keywords increased, with the most significant rise observed in the keywords "dynamics," "model," and "prices." In 2022, "dynamics" reached a frequency of 17, "model" 15, and "prices" 9, representing their highest occurrences in the dataset. These numbers indicate a growing emphasis on these topics in academic research.

Overall, the data shows that the topics of dynamics, models, and prices have become more prevalent in academic articles over the years. Research in these areas has gained more attention and importance in the academic community. Additionally, the data suggests a growing interest in other keywords such as "prediction," "volatility," "behavior," "information," "market," "risk," and "traders," all of which have seen increased frequency, highlighting their relevance in contemporary research.

3.3 Countries and affiliations

Chinese affiliations represent the majority of our dataset, followed by American affiliations. This insight highlights the leading role of Chinese and American research in artificial intelligence-based dynamic pricing.

Figure 3 provides detailed information about the corresponding author's country. (See also Ali et al. (2023); Md Khudzari et al. (2018); Rahman et al. (2023) for more detailed insights among countries by lines.) The figure lists the number of articles for each country, the number of single-country publications (SCP), and the number of multiple-country publications (MCP). China produces the highest number of articles, with 26 articles and 30.8% of these being multiple-country publications. The USA follows with 19 articles and 21.1% multiple-country publications. The remaining countries each contribute between 1 and 5 articles.

Figure 3 clarifies article production and international collaborations. It reveals that China and the USA lead publications and actively collaborate in international research.

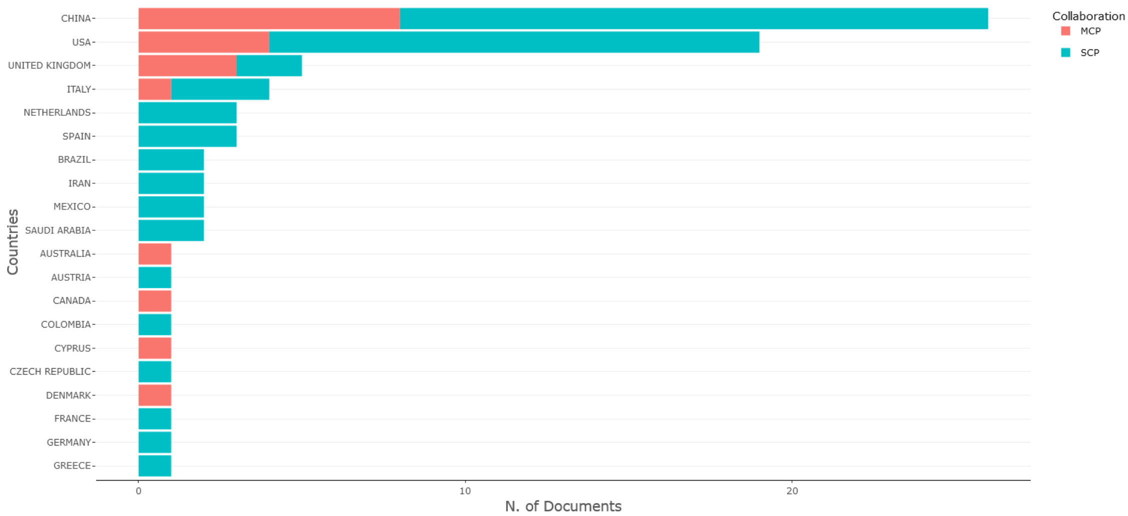

Figure 3: Corresponding author's country

The USA and China are the countries with the most articles. The USA had the highest number of articles for most years, except in 2021 and 2022 when China significantly surpassed the USA. The UK consistently had fewer articles than the USA and China but showed a steady increase from 2008 to 2022. Countries like the Netherlands, Spain, Italy, Iran, and Saudi Arabia consistently have fewer articles compared to other countries.

Table 3 displays the ranking of the most cited countries. The table shows the total citations each country has received. The United States leads with 738 citations, followed by China with 361 citations, and Australia with 310 citations. The remaining countries have fewer citations, with Brazil at 230, the United Kingdom at 97, and other countries like India, Malaysia, Iran, Italy, and Greece receiving less citations.

Table 3: Most cited countries

Country	Total citations
USA	738
CHINA	361
AUSTRALIA	310
BRAZIL	230
UNITED KINGDOM	97
INDIA	69
MALAYSIA	60
IRAN	54
ITALU	49
GREECE	27

Figure 4 presents the collaborative world map. Countries producing articles appear in blue, with darker blue indicating more articles. The USA shares 6 articles in collaboration with China and 3 with the United Kingdom. In contrast, all other countries either collaborate on a single article or do not collaborate at all. Figure 4 underscores the predominant roles of the USA and China in international research collaborations.

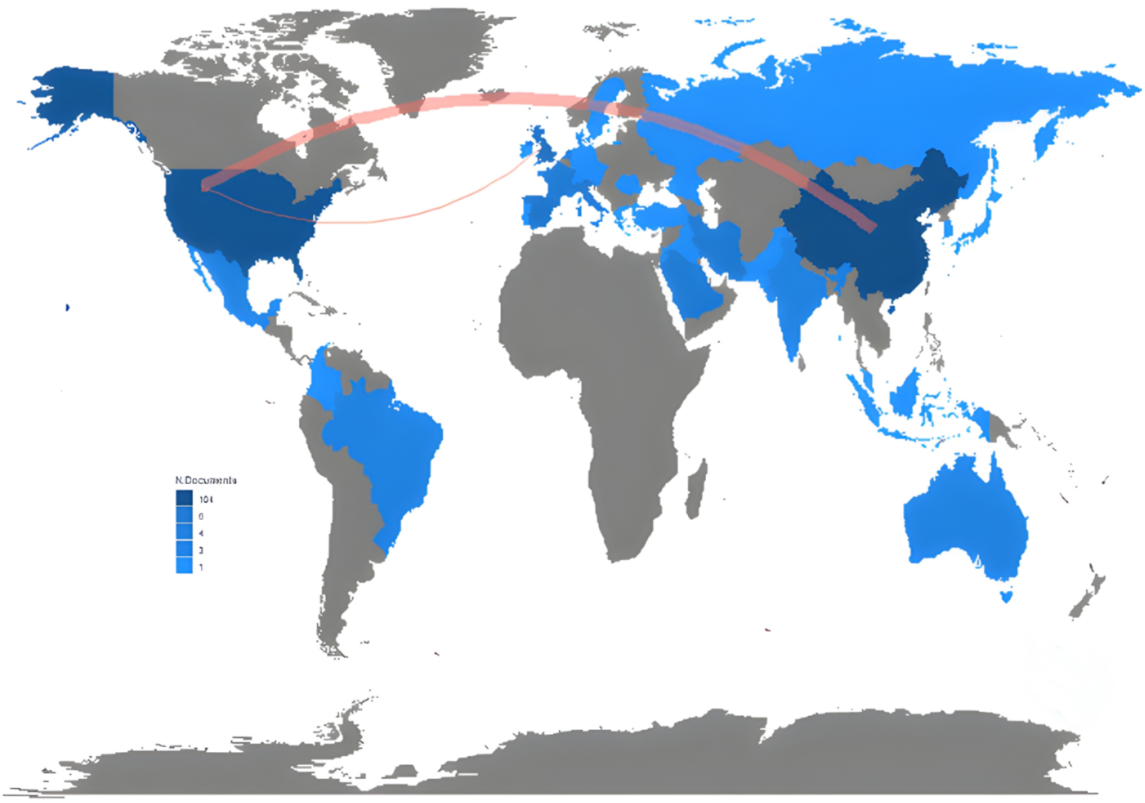

Figure 4: Collaborative world map

In summary, China has emerged as the leading producer of articles on artificial intelligence-based dynamic pricing, particularly in recent years. However, the USA remains the most prominent country in terms of citations, receiving significantly more than other countries. Both China and the USA engage in extensive international collaborations.

It is important to note that the apparent outperformance of China may be underestimated, as this analysis only includes English articles from international peer-reviewed journals. Including articles published in Chinese journals would further reinforce China's leadership in this field.

3.4 Clusters

Figure 5 groups the keywords into five main clusters: financial modeling and price forecasting, market dynamics, commodity market, and behavior and decision-making.

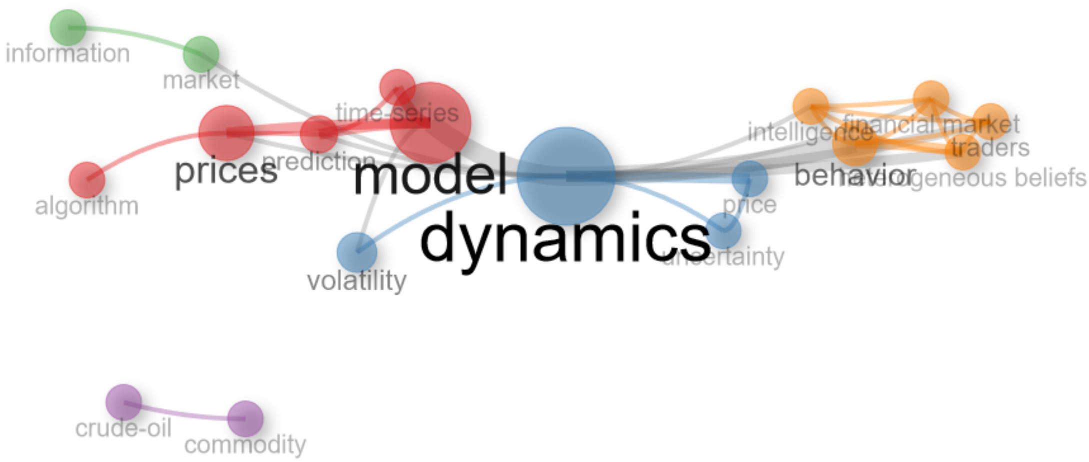

Figure 5: Cluster of keywords

We observe the following clusters:

- *Cluster 1: Financial modeling and price forecasting.* This cluster includes the keywords "model," "prices," "prediction," "algorithm," and "time-series." The keywords in this cluster exhibit high betweenness values, with "model" (11.68) and "prediction" (3.12) being particularly notable. This insight suggests these keywords act as critical bridges within the network, connecting various subfields. High closeness values further indicate that these keywords are centrally located, allowing for quick dissemination of information across the network. The high PageRank values, especially for "model" (0.089) and "prices" (0.060), highlight their significant influence in ranking other keywords. This cluster's prominence underscores the essential role of financial modeling and price forecasting in commodity markets, reflecting an intense research focus on accurate predictions and financial algorithms.

- *Cluster 2: Market dynamics.* This cluster contains keywords such as "dynamics," "market," "price," "volatility," and "uncertainty." The keyword "Dynamics" stands out with exceptionally high betweenness (79.2) and the highest PageRank (0.173), indicating its crucial role in connecting and influencing other keywords. The high closeness value (0.056) of "dynamics" also suggests it is central within the network. Keywords like "volatility" and "uncertainty" have moderate closeness values, emphasizing their role in the interconnected study of market behavior. This cluster's data indicates a strong emphasis on understanding and modeling market behaviors and fluctuations, which are critical for strategic decision-making and policy development.

- *Cluster 3: Commodity market.* This cluster includes the keywords "commodity" and "crude-oil." Both keywords in this cluster exhibit high closeness values (1), indicating they are central within their specific sub-network. However, their low betweenness and PageRank values suggest they are more isolated from the broader network. This cluster's configuration reflects a specialized focus on commodity markets, mainly crude oil, highlighting the need for targeted research in this sector. The centrality of these keywords within their cluster points to their importance in niche studies, though they are less interconnected with other broader research themes.

- *Cluster 4: Behavior and decision-making.* This cluster encompasses keywords such as "behavior," "traders," "heterogeneous beliefs," "intelligence," and "financial market." Keywords in this cluster exhibit low betweenness, closeness, and PageRank values, indicating they are separate from the broader network. However, "behavior" and "traders" have relatively higher PageRank values (0.068 and 0.059, respectively), suggesting some influence within their subfield. This cluster's lower centrality and connectivity might indicate that research on behavior and decision-making needs to be more cohesive and emerging within the context of commodity markets. Despite this, these keywords signify an interest in the psychological and strategic aspects of market participants, which could become more prominent as the field evolves.

A notable observation is the high betweenness and closeness values for the keywords in Clusters 1 and 2, indicating their centrality and importance in the network. This suggests that financial modeling and price forecasting, as well as market dynamics, are key areas of research in the field of commodity markets. The centrality of these keywords underscores their critical role in facilitating information flow and connecting various research themes.

In particular, the keywords "model," "prices," "prediction," and "volatility" in Cluster 1 have high values across all three metrics (betweenness, closeness, and PageRank), highlighting their strong influence on other keywords in the network. This idea reflects the crucial importance of accurate financial modeling and forecasting in commodity markets, where investors and traders rely heavily on precise predictions to inform their strategies and decisions.

Cluster 2, encompassing market dynamics-related keywords, also shows high values in both betweenness and closeness metrics. This link indicates that understanding market behaviors and fluctuations is central to the field, with significant implications for policy development and strategic decision-making. The relatively high PageRank values further emphasize the importance of these keywords in shaping the overall research landscape.

Keywords in Cluster 4, related to behavior and decision-making, show lower values in all three metrics, suggesting they are less central and influential within the broader network. This point might imply that research in this area is still developing or has a more specialized focus. Nevertheless, these keywords highlight essential aspects of market participant behavior and decision-making processes, which could gain prominence as the field matures.

In summary, Figure 5 provides valuable insights into the relationships between keywords and their grouping based on centrality and closeness within the network. It helps to better understand the various research areas and their organization, highlighting the prominence of financial modeling, price forecasting, and market dynamics in commodity markets research.

3.5 Thematic map

The thematic map shown in Figure 6 provides a visualization of the clustering of keywords from a dataset of 95 articles. The position of each keyword on the map is determined by its relevance degree (betweenness centrality) and development degree (closeness centrality). Keywords with high relevance and high development are located in the upper right quadrant, while those with low relevance and low development are in the lower left quadrant. The keywords are grouped into clusters, each representing a specific research theme.

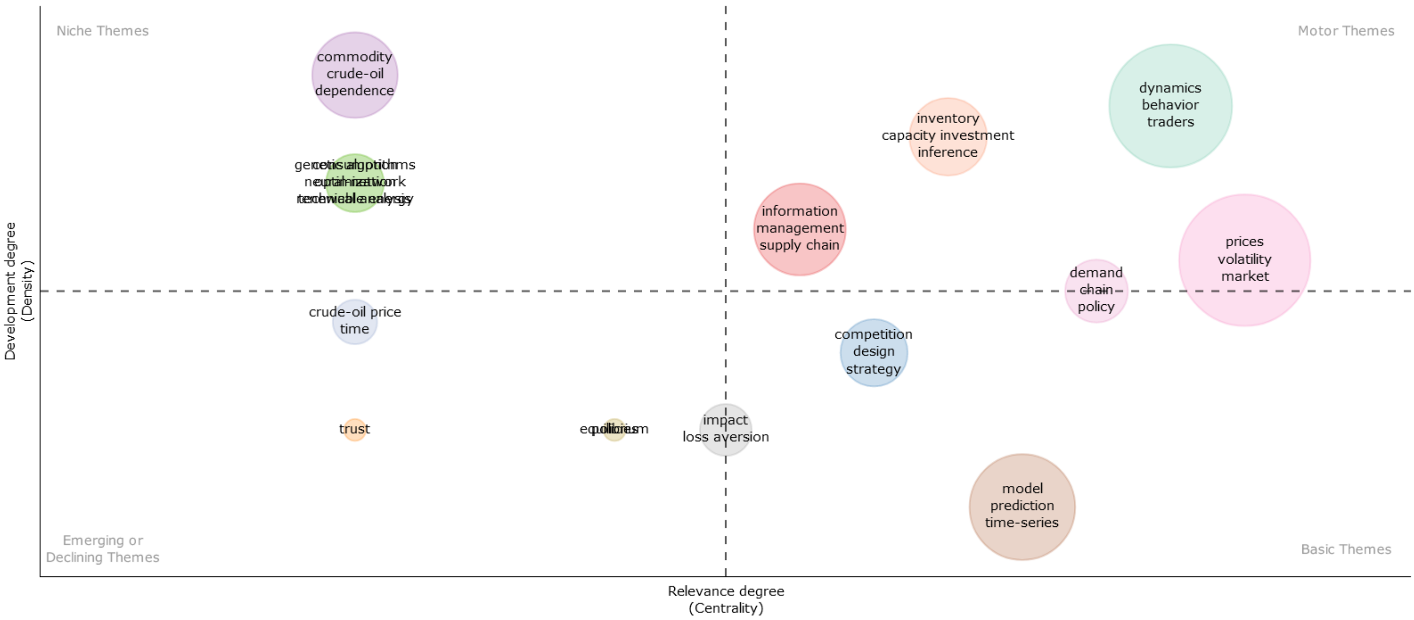

Figure 6: Thematic map

Using this map, we can categorize four keywords groups: emerging or declining themes, basic themes, niche themes, and motor themes. These categories provide insight into the state of the literature and can guide future research.

Emerging or declining themes are characterized by low relevance and development. Keywords in this category include policy, demand, chain, information, management, supply chain, innovation, product, and systems. While policy appears to be a declining theme due to its well-developed but low activity status, keywords in the information cluster, such as innovation and product, are emerging themes that still need to be well-established in previous literature but show growth potential.

Basic themes are fundamental to the field and are well-developed but less central. Keywords in this category include prices, risk, algorithm, liquidity, markets, selection, simulation, exchange, investment, power, price fluctuations, zero-intelligence, model, prediction, time-series, and spot. Selection optimization is a growing theme, whereas prices risk algorithm represents a more established and extensively covered topic. The high centrality metrics of these keywords highlight their foundational role in financial modeling and market analysis.

Niche themes are highly specialized and have high relevance but lower development. Keywords in this category include genetic algorithms, neural-network, technical analysis, policies, and trust. These themes are still gaining traction in the literature but hold significant potential for future growth and development.

Motor themes are the driving forces in the field, with high relevance and development. Keywords in this category include market, simulation, investment, commodity, crude-oil, dependence, behavior, traders, and price. These highly influential themes have extensive coverage in the literature, indicating their critical role in shaping the research landscape.

The detailed analysis of clusters provides further insights. The information cluster, characterized by keywords like information, management, supply chain, innovation, product, and systems, exhibits high betweenness centrality values. Information and management are particularly notable as crucial bridges within the network and facilitators of information flow and connection between various subfields. The high closeness and PageRank values further indicate their central role and influence in the network.

The competition cluster includes keywords like competition, design, and strategy. Keywords in this cluster, such as competition and design, exhibit significant betweenness centrality, indicating their importance in linking different research areas. The closeness and PageRank values highlight their central position and influence in the network, suggesting a vital research focus on competitive strategies and design innovation.

The consumption cluster focuses on consumption patterns, optimization techniques, and renewable energy, with optimization showing the highest betweenness centrality. These keywords are moderately central in the network, indicating their growing importance in research related to sustainable consumption and optimization processes.

The commodity cluster, which includes keywords like commodity, crude-oil, dependence, equity, financialization, returns, and stock-market, shows that commodity and crude-oil have high closeness values, suggesting their centrality within the commodity market sub-network. However, their lower betweenness and PageRank values indicate these themes are more isolated but highly specialized, reflecting targeted research on commodity markets, especially crude oil.

Finally, the dynamics cluster includes keywords such as dynamics, behavior, traders, price, heterogeneous beliefs, intelligence, financial market, resolution, and speculative markets. The keyword dynamics stands out with extremely high betweenness centrality, highlighting its crucial role in the network. This cluster reflects a comprehensive understanding of market dynamics, participant behavior, and speculative activities.

By categorizing the keywords into these groups, we can identify gaps in the literature that need to be filled and guide future research. Additionally, by focusing on the motor themes, researchers can ensure that their work remains at the forefront of the field and is well-aligned with current trends and developments. Overall, this thematic map provides a useful tool to understand the state of the literature and guiding future research in the field.

4 Discussion

This section presents a comprehensive framework for the eight distinct categories of relationships between artificial intelligence and dynamic pricing. These categories emerged from an extensive review and systematic classification of the literature, which also identified the associated mechanisms for each type. Although each relationship has sufficient theoretical support and unique processes to warrant individual treatment, there are inevitable overlaps between categories due to the interdependence between artificial intelligence and dynamic pricing processes. We provide a conceptual framework illustrating how each relationship category manifests through its associated mechanisms.

4.1 Agent-based models

One of the most crucial topics that arose from the bibliometric analysis was the use of agent-based frameworks and models to study market dynamics. Numerous studies have shown that agent-based frameworks and models are beneficial in assessing market dynamics (Cliff and Bruten, 1999; Lunde and Torkar, 2020; Tai et al., 2018; Yeh, 2008; Yeh and Yang, 2010, 2013). Through these models and frameworks, it becomes feasible to explore how market performance is influenced by various factors like price caps, trading skills, and learning preferences.

The six papers showcased in this section delve into various facets of agent-based modeling and the analysis of economic systems. These topics span from investigating the effects of price limits on stock markets (Yeh and Yang, 2010, 2013) to exploring the influence of cognitive abilities on market behavior and performance (Tai et al., 2018; Yeh, 2008), and utilizing news sentiment for GDP prediction (Lunde and Torkar, 2020).

Yeh and Yang (2010, 2013) both examine the impacts of price limits on stock market behavior, but they employ distinct methodologies and reach slightly different outcomes. On the one hand, Yeh and Yang (2010) suggest a model based on agents and shows that suitable price limits can lower volatility and enhance overall welfare. On the other hand, Yeh and Yang (2013) evaluates various propositions and identifies indications of postponed price determination and trading disruptions linked to the level of price limits.

Tai et al. (2018); Yeh (2008) both explore the influence of cognitive capabilities on market conduct and outcomes, yet they concentrate on distinct facets of cognitive aptitude and employ diverse experimental arrangements. Yeh (2008) delves into the repercussions of various learning styles and comprehension representations on market efficiency and price revelation. Conversely, Tai et al. (2018) specifically scrutinizes working memory capacity and its effects on market performance within a double auction setting involving artificial traders. Both studies reveal notable variations in market behavior and performance based on cognitive ability, although their findings propose dissimilar specific factors that contribute to these distinctions.

Cliff and Bruten (1999) takes a more theoretical approach, arguing that economic interactions represent behaviors of collective social adaptation and proposing the use of adaptive behavior research to build predictive models of market models. The paper summarizes previous work in experimental economics and presents results from experiments where simple autonomous agents exhibit human-like collective market behaviors.

Lunde and Torkar (2020) is the sole article in the analysis that centers on the prediction of GDP, employing dynamic factor models and integrating news sentiment as a predictor. The study concludes that incorporating news sentiment improves forecasts and outperforms univariate autoregression.

Overall, while the papers in this review focus on different aspects of economic modeling and analysis, they all demonstrate the importance of considering heterogeneity, adaptive behavior, and external factors such as news sentiment in understanding economic systems and making predictions about their behavior.

4.2 Consumption

Consumption is another theme that surfaced during the bibliometric study (Al Janabi, 2022a; Johana Marin-Rodriguez et al., 2022; Makhadmeh et al., 2021; Sunar and Swaminathan, 2022; Zhu et al., 2021). One literature review paper (Johana Marin-Rodriguez et al., 2022) and four research papers (Al Janabi, 2022a; Makhadmeh et al., 2021; Sunar and Swaminathan, 2022; Zhu et al., 2021) are associated with this topic. Through a scientometric review, Johana Marin-Rodriguez et al. (2022) looked at the dynamic link between financial assets and oil prices. She identified prospective study areas to quantify the relations more rigorously.

Al Janabi (2022a); Makhadmeh et al. (2021); Zhu et al. (2021) all discuss various aspects of consumption in optimization problems in the fields of finance and engineering. In the realm of finance, Al Janabi (2022a); Zhu et al. (2021) delve into optimization problems related to liquidity risk and pairs trading, respectively. Al Janabi (2022a) concentrates on creating algorithms for modeling trading volumes during the closeout period, while Zhu et al. (2021) explores optimal pairs trading strategies with constraints on symmetric and non-symmetric trading. Both studies employ mathematical models and empirical analyses to underpin their conclusions, with the shared goal of enhancing financial performance.

On the flip side, Makhadmeh et al. (2021) discusses an optimization issue in the field of engineering, specifically focusing on the power scheduling problem in smart homes. The study introduces a hybrid methodology that merges the min-conflict algorithm with grey wolf optimization to enhance the efficiency of power scheduling. Notably, this paper stands out as the sole one among the trio that tackles an engineering challenge instead of a financial one.

Expanding the scope of this varied compilation, Sunar and Swaminathan (2022) provides an overview of the progress made in utilizing operations management for socially significant matters such as weather phenomena, food scarcity, energy deprivation, and restricted healthcare availability. The authors delve into studies concerning sustainable planet endeavors, agriculture, and public health, while also pinpointing potential avenues for future research, with a particular emphasis on innovative business strategies and technologies such as blockchain and artificial intelligence. This article distinguishes itself by exploring the application of operations management in tackling crucial social and environmental issues, broadening the focus beyond the conventional optimization challenges encountered in finance and engineering.

Despite these differences, the four papers share some similarities. For instance, all four papers propose novel optimization methods or review significant advancements in their fields. Moreover, all four papers employ mathematical models to some degree and carry out empirical studies to assess the efficacy of their proposed methods or reviewed advancements. Lastly, all four papers strive to enrich the optimization and operations management literature in their specific domains and offer perspectives for future research.

4.3 Crude-oil

The crude-oil price theme consists of three papers (Azadeh et al., 2014; Huang and Wu, 2018; Syriopoulos et al., 2021). Recent developments in artificial intelligence and machine learning algorithms have been incorporated into this theme to address difficulties in forecasting oil prices. Studies have employed artifiicial intelligence methods such as deep learning and multiple kernel machines, along with a directed acyclic graph for data representation, to develop new strategies for predicting the dynamics of oil prices. The comparative evaluation results against standard time-series forecast models showed robust outperforming of traditional models. Combining deep learning, multiple kernel machines, and DAG for data representation has enabled the successful prediction of oil prices.

All three papers emphasize the importance of accurate predictions. Syriopoulos et al. (2021) focuses on developing a novel framework for predicting new building ship prices in different vessel types and shipping markets using artificial intelligence and machine learning algorithms. Azadeh et al. (2014) investigates the viability of the organizational cybernetics systems approach to model the Iran broiler industry and employs artificial neural networks and system dynamics simulation methods to enhance the system's regulation against oscillations. Huang and Wu (2018) proposes a strategy to predict oil prices using deep (hierarchical) multiple kernel learning by exploiting information from oil, gold, and currency markets. By providing accurate predictions, the results of these papers can aid decision-makers and stakeholders in developing effective strategies, mitigating risks, and optimizing their resources.

Each paper employs advanced modeling techniques to achieve its prediction goals. Syriopoulos et al. (2021) utilizes the support vector regression, a popular method in machine learning that aims to minimize prediction errors through kernels to predict new building ship prices. Azadeh et al. (2014) employs artificial neural networks, an algorithm inspired by how the human brain processes information, to enhance the regulatory functions of the broiler industry. Huang and Wu (2018) uses deep multiple kernel learning, a technique that combines deep learning and multiple kernel machines to predict oil prices by exploiting information from multiple sources. These advanced and sophisticated modeling techniques require deep understanding and expertise from the researchers.

The papers differ in their problem definition, context, and data sources. While Huang and Wu (2018); Syriopoulos et al. (2021) address problems related to energy and transportation sectors, Azadeh et al. (2014) focuses on the broiler industry in Iran. Furthermore, the data sources used for each paper are different. Syriopoulos et al. (2021) relies on shipping market data, while Azadeh et al. (2014) collects data from the Iranian broiler industry, and Huang and Wu (2018) uses information from various energy and financial markets. The papers also differ in their evaluation metrics and performance measures. Syriopoulos et al. (2021) uses statistical criteria to comparatively evaluate the predictive performance of the support vector regression model against the ARIMA models. Azadeh et al. (2014) does not provide an explicit evaluation metric but suggests that the results of their model outperform traditional methods. Huang and Wu (2018) evaluates the performance of their model using empirical data from the energy and financial markets and shows that their model outperforms traditional methods and significantly reduces forecasting errors.

The three papers share many similarities in their common interest in developing accurate prediction models using advanced techniques. However, their problem definition, data sources, and evaluation metrics differ. Despite their differences, the papers offer valuable contributions to their respective fields and provide insights that can aid decision-making, risk management, and resource optimization in complex systems. Future research could explore the application of these methods to other domains and validate their results using real-world data.

4.4 Design

This section's design theme comprises four papers presenting various optimization techniques and their applications in diverse areas. The first paper by Juda and Parkes (2009) focuses on applying option-based optimization techniques in solving linear and non-linear problems, with potential applications in marketplaces. The second paper by Luqman et al. (2019) presents a targeted firefly algorithm for solving optimization problems in agricultural communities. The third paper by Ma et al. (2021) proposes a reputation-based optimization approach for engineering design problems. Finally, the fourth paper by Cao et al. (2024) explores adaptive recommendation algorithms in the context of competition among firms for users' attention.

Cao et al. (2024); Juda and Parkes (2009); Luqman et al. (2019); Ma et al. (2021), are all research works that investigate optimization issues in various design fields. Although each article concentrates on a specific domain, they have commonalities in their optimization methodologies. Nevertheless, there are also significant distinctions that distinguish each study.

The main commonality among the papers is their utilization of optimization techniques for problem-solving. Specifically, Cao et al. (2024); Juda and Parkes (2009); Ma et al. (2021) all employ mathematical models to discover optimal solutions. In Juda and Parkes (2009), the focus is on an auction scenario where multiple buyers engage in sequential auctions for different items. The authors introduce an options-based approach that coordinates pricing and winner determination. Similarly, Ma et al. (2021) examines interactions between sellers and buyers in online markets. Through simulation methods, they investigate how pricing and reputation levels impact the likelihood of sellers making sales. Cao et al. (2024) utilizes a continuous-time bandit model to study firms recommending content to consumers who use multiple platforms, emphasizing the balance between exploration and exploitation in recommendation algorithms. Both Juda and Parkes (2009); Ma et al. (2021), and Cao et al. (2024) leverage mathematical models to enhance market efficiency and user engagement.

Luqman et al. (2019), also employs optimization methods, this time within the realm of agriculture. The researchers introduce a new algorithm, known as the targeted showering optimization algorithm, to address linear, nonlinear, and multi-objective challenges in domains like agriculture and engineering. By emulating the targeted coverage of irrigation equipment, the algorithm translates real-world processes into a computational setting driven by artificial intelligence to identify the best solutions. In this context, optimization is applied to enhance overall revenue and reduce nitrogen loss in a simulation of the ideal crop rotation for organic farming in Slovenia.

Despite their common use of optimization techniques, each paper employs different mathematical models suited to their specific area of study. The Juda and Parkes (2009) auction problem uses the Vickrey auction method and options-based solutions, while Ma et al. (2021) employs a reputation-price ratio model for online markets. Meanwhile, Luqman et al. (2019) uses the targeted showering optimization algorithm, a metaheuristic algorithm inspired by irrigation tools, for nonlinear and multi-objective optimization. Cao et al. (2024), on the other hand, utilizes a continuous-time bandit model to balance the exploration and exploitation trade-offs in recommendation systems under varying market conditions.

Another significant contrast among the papers is in the domains they investigate. Juda and Parkes (2009) centers on the electronic marketplace, whereas Ma et al. (2021) delves into economic interactions with restricted information. The study by Luqman et al. (2019) focuses on agricultural optimization. Conversely, Cao et al. (2024) delves into the effects of competitive dynamics on personalized recommendation systems in digital markets. This notable disparity in research areas necessitates varied optimization strategies, as evidenced by the utilization of different mathematical models and algorithms.

Finally, disparities are present in the empirical assessments of the models developed in each paper. The Juda and Parkes (2009) empirical study demonstrates that the proposed options-based solution enhances efficiency and revenue compared to eBay's current market design. Ma et al. (2021) conducts simulations to explore the impact of various reputation levels and pricing on interactions between sellers and buyers in the online marketplace. Luqman et al. (2019) assesses the effectiveness of the targeted showering optimization algorithm by testing it on well-known benchmark functions and examining its suitability for optimizing crop rotation in Slovenian organic farming. Conversely, Cao et al. (2024) scrutinizes the consequences of forward-looking versus myopic recommendation strategies in competitive and monopolistic environments, highlighting how these strategies influence firms' incentives and user welfare.

Although Cao et al. (2024); Juda and Parkes (2009); Luqman et al. (2019); Ma et al. (2021) pursue a shared goal of discovering the best solutions via mathematical modeling and optimization, they vary in the domains they investigate, the mathematical models and algorithms employed, and the empirical assessments. Nevertheless, every publication adds to the comprehension of optimization in unique sectors.

4.5 Dynamics

The dynamics theme comprises fifteen papers that explore various topics related to prediction. Time series analysis is utilized in multiple papers, such as the work by LeBaron et al. (1999), to comprehend the fundamental dynamics of real markets. Techniques like chaotic mapping, firefly algorithm, and support vector regression prove effective in predicting stock market prices, as evidenced in the studies by Wang et al. (2018) and Zhang et al. (2019). The paper by Ponta et al. (2012) adopts the delay coordinate embedding method to reconstruct phase space dynamics. Additionally, the paper by Hong et al. (2022) employs the chaotic firefly algorithm to optimize support vector regression hyperparameters. Furthermore, the paper by Methenitis et al. (2020) utilizes the structural risk minimization algorithmic framework to enhance prediction accuracy.

Several papers utilize machine learning models to identify intricate patterns in different applications. Support vector machines and neural networks are popular artificial intelligence algorithms employed to enhance prediction precision, as evidenced in the papers by Kazem et al. (2013) and Yang and Mehmed (2019). Moreover, data fluctuation networks and other artificial intelligence algorithms are leveraged to further improve forecast accuracy, as illustrated in the paper by Garcia Cabello (2022). We will now delve deeper into each of these papers.

LeBaron et al. (1999) introduces a computer-simulated stock market in which artificial intelligence algorithms function as traders and provide forecasts. This market mirrors various characteristics of actual markets, including fundamental and technical predictability, volatility persistence, and leptokurtosis. On the other hand, Zhang et al. (2019) describes a simulation of high-frequency market data through the Genoa Artificial Stock Market. In this simulation, agents lacking intelligence trade a risky asset for cash. Both studies employ computer simulations to investigate aspects of market behavior, albeit through distinct methodologies.

Kazem et al. (2013); Wang et al. (2018) both concentrate on prediction techniques, employing algorithms like firefly optimization and artificial intelligence methods such as BPNN, RBFNN, and ELM to anticipate forthcoming data regarding crude oil prices. While Kazem et al. (2013) introduces an innovative prediction model for stock market prices, incorporating the firefly algorithm, chaotic mapping, and support vector regression, Wang et al. (2018) explores a hybrid strategy that merges a dynamic fluctuation network with artificial intelligence methods to forecast the Baltic Dry Index.

Henrique et al. (2019) delves into the importance of machine learning models in forecasting financial market prices through a bibliographic survey method, classifying markets, assets, techniques, and variables from 57 sources. The research examines market information from North America and indicates that support vector machines and neural networks are the predominant models for prediction. Conversely, Garcia Cabello (2022) introduces a mathematical and artificial intelligence framework for forecasting price trends in markets influenced by lobbying, with a specific focus on precise predictions of olive oil prices in Andalusia, Spain.

Ponta et al. (2012); Yang and Mehmed (2019) both explore the impacts of different market factors on shipping freight rates. Ponta et al. (2012) delves into the enhancement of shipping freight rate forecast accuracy through forward freight agreements, whereas Yang and Mehmed (2019) contrasts the consequences of zero-intelligence trading and herding in a double auction market.

Methenitis et al. (2020); Wah et al. (2017) both explore the influence of market performance on trader welfare. Wah et al. (2017) delves into the effects of market making on market performance concerning allocative efficiency and gains from trade for background traders, whereas Methenitis et al. (2020) investigates the effects of buyers' rationality on retail markets with identical items.

Bredin et al. (2021); Hong et al. (2022) both explore the connection between equity market uncertainty and the energy market. Bredin et al. (2021) shows that Nelson-Siegel factors derived from the term structure of WTI oil futures can predict WTI holding period returns. On the other hand, Hong et al. (2022) investigates the impact of equity market uncertainty on the energy market through an asymmetric Granger causality test, which accounts for both positive and negative shocks.

de Araujo Lobao et al. (2018); Yu and Chen (2018) both introduce innovative approaches for predicting prices. de Araujo Lobao et al. (2018) examines the efficacy of evolutionary algorithms in deriving symbolic solutions for stochastic differential equations, whereas Yu and Chen (2018) introduces a proficient system for forecasting oil prices through a supervised neural network.

Finally, Khashman and Carstea (2019); Methenitis et al. (2020) delve into the mathematical relationships among different market factors. Khashman and Carstea (2019) investigates the influence of uncertainty in the equity market on the energy market through a Granger causality test. On the other hand, Methenitis et al. (2020) introduces a model based on mathematics and artificial intelligence to forecast price trends in markets influenced by lobbying.

The chosen papers provide a variety of perspectives on financial markets, predictive models, and market dynamics. While each paper presents its own distinct methodology and findings, together they illustrate the intricate relationship among market variables, trader actions, and forecasting methods. These investigations establish a solid groundwork for forthcoming research endeavors.

4.6 Information

The information theme provides a comprehensive analysis of current research on the role of digitalization and AI in reshaping dynamic pricing strategies across various sectors. The impact of digitalization on optimizing pricing tactics and enhancing business-to-business transaction profitability is highlighted by Leung et al. (2019). They emphasize the role of AI in increasing flexibility in value capture, a viewpoint echoed by De Giovanni (2019), who explore dynamic pricing's capacity for automation and real-time data application in digital markets.

Several studies explore the complexities introduced by AI-powered pricing algorithms. Calvano et al. (2020) and Klein (2021) investigate the potential for AI algorithms to autonomously establish supra-competitive pricing, raising apprehensions about algorithmic collusion within oligopolistic markets. This sentiment is reinforced by Brown and MacKay (2023), where the implications of automated pricing on competition, including increased price levels and dispersion, are examined. The empirical study by Assad et al. (2024) further corroborates these impacts, showing notable effects on competition margins in Germany's retail gasoline sector. Contrastingly, Johnson et al. (2023) argue for the potential of AI-driven platform designs to enhance market competition and consumer benefits, offering a mechanism to counteract collusive behaviors.

Privacy and trust present critical concerns within dynamic pricing frameworks. Chen et al. (2022) propose privacy-preserving techniques utilizing differential privacy to balance revenue and customer data security, contrasting the broader overview provided by Cohen (2018) regarding big data's transformative role and associated privacy challenges. Trust dynamics in pricing are indirectly addressed by Cheng et al. (2023), who draw correlations between trust patterns and transaction outcomes in ride-sharing contexts.

Ethical and practical considerations remain a focal discussion point, with Kopalle et al. (2023) underscoring the balance between personalization, revenue strategies, and ethical implications. This balance is similarly addressed by Li and Li (2022), who assess potential negative outcomes of AI automation on supply chains. Moreover, Miklós-Thal and Tucker (2019) explore the dual-edged nature of AI in forecasting, acknowledging both the potential for consumer benefit through price reduction and the risk of collusion. Additionally, the integration of Operations Management in making cities smarter aligns with these discussions (Mak, 2022).

The adoption of dynamic pricing is extending into emerging territories, as presented in studies such as Agarwal et al. (2022) and Kong et al. (2021), which highlight optimization in digital transactions and logistics. Furthermore, innovative applications by Yuan et al. (2021) and Yang et al. (2022) leverage historical data and quality perception to optimize auctions and reduce waste in fresh produce markets.

Methodological exploration continues with Mirrokni et al. (2020), who delve into non-clairvoyant dynamic pricing strategies, favoring uninformed approaches in less predictable consumer environments. On the other hand, Deng et al. (2004) focus on the informed application of AI to price perishable goods, underscoring the importance of demand forecasts. In line with this, Li and Zheng (2024) stress the importance of external data in dynamic pricing models where demand functions are initially unknown, facilitating revenue maximization. More recent innovations apply reinforcement learning for hotel pricing (Tuncay et al., 2024), addressing specific sector needs and improving predictions.

Enhancements in predictive analytics and data dynamics form another pivotal theme, as showcased in Garcia et al. (2022), who employ algorithmic recommendations for improved demand elasticity estimates. Gurkan and de Véricourt (2022) further detail the AI Flywheel effect, highlighting the challenges of managing data acquisition and profitability trade-offs. These insights are vital for developing refined data utilization strategies essential for maximizing AI efficacy.

In summary, these studies collectively emphasize AI's transformative capacity in dynamic pricing, promoting efficiency and competitiveness. Nonetheless, they also call for awareness of ethical, competitive, and regulatory challenges, advocating for frameworks that ensure AI benefits both businesses and consumers in the evolving digital landscape.

4.7 Market

In the market theme, financial modeling is used to analyze financial markets and understand their dynamics. Slanina (2008) reviews agent-based models of financial markets, highlighting their limitations and proposing possible avenues for improvement. Marowka et al. (2020) investigate using factor-augmented vector auto-regressive models to capture the dynamic relationship between macroeconomic variables and stock returns. Liu et al. (2014) propose a behavior model that captures the collective behavior of stock traders and its impact on market dynamics. Martinazzi et al. (2020) investigate the implications of market dynamics for new technologies such as the Lightning Network, a layer-two protocol that facilitates faster and cheaper Bitcoin transactions. Mathieu and Morvan (2019) propose a deterministic approach to modeling stock return processes using generative adversarial networks, which can capture the complex, non-linear relationships between market variables. Finally, Tan et al. (2022) investigate the use of deep reinforcement learning for optimal trading strategies in financial markets. We now discuss each paper further.

Slanina (2008) examines models of interacting particles in one dimension and how they can be used to model stock market fluctuations. This paper highlights the importance of understanding how buy and sell orders interact to impact market prices. Marowka et al. (2020) takes a different approach and considers how vector auto-regressive models can be used to study commodity markets, specifically the soybean crush spread. This paper emphasizes the importance of an appropriate time series model with cointegration to account for the time-varying effects on the spread.

Liu et al. (2014) focuses on the determinants of option implied volatility smile and how traders' behavior can explain it. Using agent-based simulation allows this paper to differentiate between zero-intelligence traders and traders' collective behavior. Meanwhile, Martinazzi et al. (2020) analyzes the Lightning Network's efficient functioning as a blockchain technology despite its underlying cryptocurrency, Bitcoin's, volatile market fluctuations.

Mathieu and Morvan (2019) takes a novel approach and introduces Deterministic Artificial Traders to illustrate that financial markets' complex system dynamics can lead to some randomness at macroscopic and microscopic levels. Finally, Tan et al. (2022) introduces DeepPricing, a data-driven model for convertible bond pricing that leverages generative adversarial networks. This model tackles the complexities of pricing hybrid instruments by accurately replicating the risk-neutral stock return process, capturing the dynamics of the underlying stock returns, and accommodating a comprehensive set of real-world convertible bond specifications.

Despite their different topics and methodologies, these papers share several similarities. For instance, they all demonstrate the importance of understanding the complex dynamics of financial markets. In addition, most papers focus on developing and proposing novel models or approaches to address particular challenges. The use of data-driven techniques, such as machine learning and agent-based simulations, is another common thread among these papers. Finally, the importance of understanding time-varying effects and path-dependency is evident in many of these studies.

However, these papers also exhibit some fundamental differences. Some papers focus more on the theoretical aspects of financial markets, such as Liu et al. (2014), while others lean more towards practical applications, such as Tan et al. (2022). Methodologically, while most papers use quantitative techniques to analyze financial data, Liu et al. (2014) takes a qualitative approach, relying on traders' behavior to explain the volatility smile. Finally, some papers focus on specific financial instruments, such as Marowka et al. (2020), which analyzes the soybean crush spread. In contrast, others have a more general focus, such as Mathieu and Morvan (2019), which broadly explores the dynamics of financial markets.

In conclusion, the papers on this theme offer diverse perspectives on financial markets, providing insights into different aspects of market dynamics, pricing, agent behavior, and novel models. While each study contributes unique findings, they all offer valuable contributions to the ongoing research of financial markets.

4.8 Price

The prices theme investigates various pricing models and their impact on the market. Contreras et al. (2018) analyze the trading volume and pricing efficiency of the Mexican stock exchange (BMV) and find that the participation of international entities leads to a significant increase in trading volume, providing valuable information for companies and investors. Tsao et al. (2021) introduce a data-driven auction design framework that leverages historical data to establish the optimal auction parameters for companies to apply in the market. Finally, Ye et al. (2021) investigates the impact of accounting for the time value of money on the evolution of a market, showing that such models can provide valuable insights for investors and traders. We discuss each of the papers further.

All papers use mathematical modeling and algorithm design as a core part of their research. Contreras et al. (2018) introduces a macromolecule-inspired algorithm to model the FOREX market. Tsao et al. (2021) employs discounted cash flows and continuous approximation to design a supply chain network model. Finally, Ye et al. (2021) constructs a classification model to improve online industrial auctions' design and proposes a data-driven auction design framework. Therefore, it is evident that all three papers focus on applying mathematical modeling and optimization techniques to solve complex problems.

All papers validate and evaluate their proposed models and algorithms using real-world data. Contreras et al. (2018) validates the ENMX algorithm's performance by comparing it with traditional econometric approaches such as the VAR model and a driftless random walk. Tsao et al. (2021) provides a numerical example and a sensitivity analysis to validate the proposed model's effectiveness. Finally, Ye et al. (2021) investigates how to improve auction design using insights from real-world industrial auction data. Therefore, it is clear that all three papers rely on real-world data to evaluate the proposed models and algorithms' performance.

However, the papers also have some notable differences. For example, Contreras et al. (2018) focuses on modeling the FOREX market's evolution, while Tsao et al. (2021) deals with supply chain network design, and Ye et al. (2021) focuses on designing auction parameters for online industrial auctions. These differences reflect the diversity of the problems addressed by each paper.

Furthermore, the methodologies and techniques used in each paper are also different. Contreras et al. (2018) uses an algorithm inspired by the behavior of macromolecules in dissolution, while Tsao et al. (2021) uses discounted cash flows and the continuous approximation approach. In contrast, Ye et al. (2021) uses a classification model to predict auction performance and proposes a data-driven auction design framework. These differences reflect the diverse problem domains of each paper and the different approaches that can solve them.

Eventually, Contreras et al. (2018); Tsao et al. (2021); Ye et al. (2021) share some commonalities, such as the use of mathematical modeling and optimization techniques and the reliance on real-world data. However, they also have notable differences, reflecting the diverse problem domains and approaches helpful in solving them.

To conclude Section 4, several major themes emerge. The themes include agent-based models, consumption, crude-oil prices, design, dynamics, and information. The papers examined in this analysis offer a comprehensive approach for researchers to understand the intricacies of the market better and facilitate businesses to optimize their pricing strategy and maximize profit from digital transactions.

5 Implications, future research directions, and conclusions

Our findings illustrate the complexity and multifaceted nature of artificial intelligence and dynamic pricing. These findings offer a comprehensive alternative approach to advancing or disrupting current efforts to develop profitable businesses. However, their intricacy also challenges their implementation on a larger scale. This complexity is further highlighted by Hansen et al. (2021), who demonstrate how misspecified machine learning algorithms can lead to supra-competitive pricing outcomes. This section will discuss the potential theoretical and practical contributions, reflect on the study's limitations, and propose future research directions based on the identified gaps.

5.1 Theoretical and practical implications

The results of this systematic literature review have important implications for both the theoretical and practical application of machine learning and artificial intelligence in different fields. The study demonstrates the close relationship between artificial intelligence and dynamic pricing and the growing importance of this area in the academic community. Section 3 presents preliminary implications, and Section 4 is more precise.

For researchers, the dominance of Chinese and American research in this field highlights the lead of these two countries in this area of study. Plus, the thematic map provides a valuable tool for researchers and practitioners in this field, helping them understand the field's current state and how it will likely develop in the future. Most articles focus on the financial sector, but other fields like energy, power scheduling, and e-commerce are also represented. Several of the articles use optimization techniques, suggesting that these algorithms are helpful tools for solving problems in various fields. For practitioners, the findings of this systematic literature review also have practical implications. For example, the use of artificial intelligence and machine learning algorithms in the financial sector suggests that these techniques can be used to predict stock market prices and help in decision-making. Similarly, applying these techniques to power scheduling problems in smart homes highlights the potential for these algorithms to improve energy efficiency and resource management.

Theoretically, the review underscores the evolving landscape of artificial intelligence and its integration into dynamic pricing mechanisms. The bibliometric analysis highlights key themes and trends, emphasizing the centrality of financial modeling and price forecasting, market dynamics, and behavior and decision-making within the literature. These clusters reflect substantial research on how artificial intelligence can be leveraged to predict and optimize pricing strategies in various markets. This aligns with the findings of Hermann (2022), who discuss the transformative impact of AI in business and marketing, while also addressing ethical considerations.

The prominence of keywords such as "model," "prices," "prediction," and "volatility" suggests a robust theoretical focus on developing predictive models and algorithms that can handle market complexities and uncertainties. These keywords' high betweenness and closeness values indicate their pivotal role in connecting different research areas, thus providing a comprehensive framework for future studies.

Furthermore, the thematic map categorizes the keywords into emerging, basic, niche, and motor themes, offering a structured approach to understanding the development and interconnections of research topics. This categorization helps identify gaps in the literature, particularly in emerging themes such as the interplay between policy, demand, and information systems, which still need to be well-established but show potential for growth.

From a practical standpoint, the insights derived from the literature review have profound implications for businesses and policymakers. The integration of artificial intelligence in dynamic pricing offers several benefits, including enhanced accuracy in price predictions, improved market efficiency, and better resource allocation. The findings suggest that businesses can leverage artificial intelligence driven models to forecast market trends, adjust pricing strategies in real-time, and optimize their competitive positioning.

The study's focus on different clusters, such as financial modeling and market dynamics, highlights practical applications in various sectors. For instance, the emphasis on keywords like "commodity" and "crude-oil" in the commodity market cluster reflects the importance of accurate price forecasting in energy markets. Businesses operating in these sectors can adopt artificial intelligence techniques to predict price fluctuations better and manage risks associated with market volatility.

Moreover, the behavior and decision-making cluster reveals consumer behavior and market psychology insights. Companies can use artificial intelligence to analyze consumer data, predict purchasing patterns, and tailor pricing strategies accordingly. This approach can lead to more personalized and effective pricing, enhancing customer satisfaction and loyalty.

The international collaboration data highlights the significant contributions of Chinese and American researchers, suggesting that businesses and policymakers in these regions are at the forefront of implementing artificial intelligence driven pricing strategies. The collaborative efforts between countries also underscore the importance of knowledge exchange and shared best practices in advancing the field.

5.2 Research gaps and future research directions

The systematic literature review reveals significant gaps in the current research on artificial intelligence and dynamic pricing, highlighting several areas for future exploration to advance academic understanding and practical application.

One of the most notable gaps is the limited exploration of ethical and privacy considerations in implementing artificial intelligence-driven dynamic pricing. While there is a growing body of work on the technical and economic aspects of dynamic pricing, more studies are needed to examine how these practices affect consumer trust and privacy. This gap is significant given the increasing regulatory scrutiny and consumer awareness regarding data privacy.

Another gap pertains to integrating artificial intelligence with emerging technologies like blockchain. While artificial intelligence has been extensively studied for its potential to optimize pricing strategies, the intersection of artificial intelligence with blockchain technology, which could enhance transparency and security in pricing mechanisms, still needs to be explored. This gap represents a promising area for future research, particularly in sectors like finance and supply chain management, where transparency and trust are paramount.

The literature also reveals a paucity of empirical studies that validate artificial intelligence models in real-world settings. Many studies rely on simulated data or controlled environments, which may not capture the complexities and unpredictabilities of actual markets. There is a need for longitudinal studies that assess the performance of artificial intelligence driven dynamic pricing models over extended periods and across different market conditions.

Additionally, there needs to be more comprehensive studies examining the impact of dynamic pricing on small and medium-sized enterprises. Most existing research focuses on large corporations with significant resources to implement advanced artificial intelligence systems. Understanding how small and medium-sized enterprises can leverage artificial intelligence for dynamic pricing and the challenges they face in doing so could provide valuable insights and support more inclusive economic growth.

To address these gaps, future research should focus on the following areas:

1. Ethical and Privacy Considerations: Researchers should investigate the ethical implications of artificial intelligence-driven dynamic pricing, examining how it affects consumer behavior, trust, and perceptions of fairness. It is crucial to develop frameworks that balance profit optimization with ethical standards and privacy protections. Studies should also explore consumer reactions to various levels of data transparency and the impact of privacy-preserving techniques.

2. Integration with Blockchain Technology: Exploring artificial intelligence and blockchain synergy can enhance the security and transparency of dynamic pricing models. Future studies should investigate how blockchain can create immutable records of pricing decisions, increasing accountability. Practical insights can be gained from case studies and pilot projects in supply chain management and finance sectors.

3. Real-world Validation of artificial intelligence Models: Empirical research testing artificial intelligence driven dynamic pricing models in real-world environments is urgently needed. Longitudinal studies tracking these models' performance over time and different market conditions would provide robust insights. Academia-industry collaborations can facilitate access to real-world data and practical implementation scenarios.

4. Support for small and medium-sized enterprises: Research should explore the unique challenges and opportunities that AI-driven dynamic pricing presents for small and medium-sized enterprises (SMEs). This includes identifying barriers to adoption and developing scalable, cost-effective solutions. Comparative studies between large corporations and SMEs can highlight adaptable best practices.

5. Multidisciplinary Approaches: Future research should adopt multidisciplinary approaches, integrating insights from economics, computer science, psychology, and ethics. This holistic perspective can help design artificial intelligence driven dynamic pricing systems that are efficient, socially responsible, and consumer-friendly.

6. Policy and Regulation: Investigating the role of policy and regulation in artificial intelligence driven dynamic pricing deployment is critical. Researchers should analyze how different regulatory frameworks affect the adoption and effectiveness of these systems and propose policy recommendations that foster innovation while protecting consumer rights.

Addressing these research gaps and pursuing these directions can significantly advance the development of effective, ethical, and inclusive artificial intelligence-driven dynamic pricing strategies. This will enhance the field's theoretical foundation and ensure that artificial intelligence benefits are widely distributed across various sectors and business sizes.

5.3 Research limitations

According to Tranfield et al. (2003) and Aria and Cuccurullo (2017), systematic literature reviews are effective in synthesizing theories and providing collective insights. However, they come with limitations, such as search strategy constraints that may exclude relevant articles based on language or mentions in titles, abstracts, or keywords (Di Vaio et al., 2020). To mitigate this risk, we utilized multiple databases (Scopus, Web of Science, and Google Scholar) and employed snowball sampling to achieve comprehensive literature coverage. Additionally, we consulted several specialists to ensure the inclusion of all critical articles.

Additionally, specific search term combinations were employed to narrow the search results to a relevant and manageable dataset (Perera et al., 2019). The primary search terms were "artificial intelligence" and "dynamic pricing," complemented by terms such as "internet of things," "big data," and "pricing," consistent with the study's objectives (Georges and Pereira, 2021). We acknowledge the potential relevance of other terms like "real-time pricing," "deep learning," "machine learning," "price discrimination," and "intertemporal discrimination" to our survey topic. Including these additional terms could have introduced diverse perspectives, but it might have compromised the study's rigor. To balance this trade-off, we limited our search to peer-reviewed articles from scholarly journals, ensuring a systematic and transparent process while focusing on the most significant part of the debate (Glock and Grosse, 2021). We excluded other forms of publications, such as books and book chapters, and restricted our search to English-language publications to adhere to standard research protocols. This exclusion policy may have overlooked some publications that could offer a more comprehensive understanding of our study.

The limitations of a literature review create opportunities for future research (De la Fuente, 1997). Future researchers could adopt a less restrictive data collection strategy, focusing on specific domains of artificial intelligence and dynamic pricing implementation. A targeted approach would allow for the inclusion of other types of publications, such as books, in the dataset (Weitzel and Glock, 2018). As previously mentioned, exploring different search terms can yield valuable insights into the relationship between artificial intelligence, dynamic pricing, and other established concepts. Including articles in non-English languages, particularly Chinese, could provide additional substantive insights, given that Chinese articles are the most numerous, even though American articles are the most cited. Additionally, combining literature-based, theory-driven research with empirical studies on the practical applications of artificial intelligence and dynamic pricing would be advantageous.

5.4 Concluding remarks

This study set out to investigate the multifaceted role of artificial intelligence in enhancing dynamic pricing strategies through a systematic literature review. By employing methodologies derived from Tranfield et al. (2003) and Paul and Criado (2020), this research compiled and analyzed 95 peer-reviewed articles from the Web of Science database. The systematic approach adhered to the 6W framework from Callahan (2014), providing a structured analysis of research trends, methodologies, and focal themes within the artificial intelligence based dynamic pricing domain. The principal findings underscore the value of artificial intelligence applications such as support vector machines, machine learning algorithms, and neural networks in dynamic pricing. These methods have significantly enhanced prediction accuracies and market behavior modeling, thereby offering a more refined understanding of pricing mechanisms and market dynamics. The comprehensive bibliometric and content analysis reveals that much of the progress in artificial intelligence based dynamic pricing research stems from the growing knowledge about artificial intelligence techniques and their adaptive capabilities. This study's contributions center around demonstrating the breadth and depth of artificial intelligence methodologies that are enriching dynamic pricing research, with particular emphasis on forecasting accuracy and enhanced decision-making frameworks.

The implications of these findings for management and policy formulation are far-reaching. For managers, adopting artificial intelligence based dynamic pricing models can enhance profitability through precise demand forecasting and inventory management, particularly in volatile markets such as commodities and perishable goods. These models facilitate real-time pricing adjustments, enabling firms to respond swiftly to market changes and consumer behavior, minimizing losses, and maximizing revenue. From a policy standpoint, integrating artificial intelligence in dynamic pricing necessitates a balanced approach to data privacy and ethics. Ensuring transparent algorithms and accountable artificial intelligence practices is crucial in fostering consumer trust and complying with regulatory standards. Policymakers should consider frameworks that encourage innovation while safeguarding consumer interests. Additionally, sector-specific guidelines could support the equitable deployment of these advanced pricing strategies, ensuring that small and medium enterprises can also leverage these technologies.

Despite the notable advancements highlighted in this study, several limitations persist. The reliance on English-language articles and the exclusion of non-peer-reviewed sources may introduce a linguistic and publication bias. Furthermore, the rapid evolution of artificial intelligence technologies means that new techniques and applications may emerge that are not covered within the time frame of this review. Future research could extend the scope of this review by including more varied data sources and considering non-English literature. Moreover, longitudinal studies examining the long-term impacts of artificial intelligence based dynamic pricing on consumer behavior, market stability, and regulatory landscapes would provide deeper insights. There is also room to explore interdisciplinary approaches, combining computer science, economics, and behavioral psychology insights to develop more holistic predictive models. Addressing these limitations can pave the way for more robust and comprehensive research, facilitating the continued evolution of artificial intelligence enhanced dynamic pricing.

Acknowledgements

The authors used ChatGPT to help write of this article. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

A Appendix

To provide a more comprehensive understanding of our systematic literature review, Appendix A proposes additional elements.

A.1 Final data from the systematic literature review

Table 4 lists the 95 articles used for the systematic literature review, summarizing the main contribution of each article.

Table 4: Selected articles for the systematic literature review

Reference	Summary
Agarwal et al. (2022)	This paper explores how customers perceive value in digital servitization, looking at the implications of contractual flexibility of price-variance, contract lengths and transparency in AI-enabled offerings.
Assad et al. (2024)	Economic theory provides mixed predictions on the impact of algorithmic pricing on competition, while empirical analysis highlights significant effects.
Al Janabi (2022a)	This paper introduces new algorithms for dynamic modeling of trading volumes during the closeout period for multi-asset portfolios, providing essential parameters to assess liquidity risk and enhance investment and risk management decisions.
Al Janabi (2022b)	This paper explores how liquidity-adjusted risk modeling improves commodity portfolio managers' ability to assess market risk and create effective portfolios in different market conditions.
Al-Fattah (2019)	This paper presents GANNATS, a hybrid model using AI, Genetic Algorithms, Neural Networks, Data Mining, and Time-Series methods to forecast West Texas Intermediate crude price volatility. It aids oil producers, consumers, investors, and traders by predicting future price movements and volatility.
Aloud (2018)	This paper suggests using Genetic Programming to create short-term trading regulations in the financial market area utilizing technical indicators and fundamental parameters in a directional-change event frame for enhanced profitability.
Azadeh et al. (2014)	This article integrates artificial neural networks and system dynamics with the viable system model to enhance the Iranian broiler industry's intelligence and regulation, especially in managing crucial cost factors like maize and soybean import tariffs.
Boer et al. (2007)	This paper investigates the difference in behavior between discrete-time and continuous-time, asynchronous agent-based simulation models when applied to a financial market with information asymmetry, and demonstrates additional information revealed in the latter models that allows agents to act upon it.
Bredin et al. (2021)	This research shows that Nelson-Siegel factors from WTI oil futures' term structure can predict future WTI returns in-sample, and this predictability remains even when adding macroeconomic indicators or oil-specific predictors.
Bredin et al. (2007)	This article explores a truth-telling approach in a dynamic two-sided market where multiple buyers and sellers trade a single good over time.
Brown and MacKay (2023)	Researchers study how pricing technology affects competition, showing that algorithms impact retailers' price adjustments.
Brunato and Battiti (2020)	Revenue Management uses data-driven modeling and optimization to boost revenue and profit. In complex hotel reservations, intelligent heuristics outperform exact optimization methods.
Calvano et al. (2020)	Algorithms are replacing humans in pricing, learning to sustain high prices through collusive strategies.
Cao et al. (2024)	The paper studies the use of bandit algorithms and reveals that competition among firms leads to more exploitation as opposed to exploration, impacting AI adoption and consumer welfare.
Chen and Lu (2016)	This paper examines "no-regret" algorithms from machine learning, investigating their impact on game dynamics, convergence, and outcome quality across different game types.
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Table 4 – continued from previous page

Reference	Summary
Cheng et al. (2023)	The study finds that in ride-sharing, order completion rate and distance boost trust, while order time and departure density reduce it.
Chen et al. (2022)	The paper presents a privacy-preserving dynamic pricing policy that maximizes retailer revenue while preventing leakage of customer information.
Cliff and Bruten (1999)	This paper proposes using experimental economics to study adaptive social behaviors in human bargaining and trading by utilizing adaptive behavior tools and equipping software agents with market adaptability.
Cohen (2018)	The study explores how big data is transforming the service industry, enabling service customization but also raising concerns about pricing, discrimination, and cybersecurity.
Collins and Thomas (2012)	This paper explores using reinforcement learning to solve a dynamic airline pricing game, comparing SARSA, Q-learning, and Monte Carlo Learning to find the Nash Equilibrium.
Contreras et al. (2018)	The proposed elastic network model for FOREX market algorithm helps companies and investors make informed decisions with just-in-time price predictions for currency pairs (e.g., EUR/USD) in the global foreign exchange market.
de Araujo Lobao et al. (2018)	This paper suggests combining genetic programming and automatic differentiation to create evolutionary algorithms capable of producing symbolic results for stochastic differential equations.
De Giovanni (2019)	This paper develops a digital supply chain game to compare static and dynamic solutions of the game between traditional and digital platforms, and evaluate two smart contracts using an AI system to determine optimal contract parameters.
Garcia Cabello (2022)	This paper introduces an AI model for forecasting market price trends influenced by lobbying, simplifying the process to probability calculations. Tested on olive oil prices, the model showed positive results.
Garcia et al. (2022)	The study presents a new framework for identifying demand elasticities in markets using algorithmic price recommendations, with applications in the hotel industry.
Gil-Bazo et al. (2007)	This study explores the consequences of alterations in the trader population and market microstructure in a simulated market populated with diverse computational agents on price activity, information circulation, and wealth allocation.
Gurkan and de Véricourt (2022)	The paper discusses how the AI Flywheel effect may be used by firms. However, too much data collection can decrease profits due to changing incentives.
Hansen et al. (2021)	Researchers examine the use of algorithms for dynamic pricing, revealing significant competitive implications.
Henrique et al. (2019)	This article reviews literature on machine learning for financial market prediction, classifying markets, assets, methods, and variables. SVMs and neural networks are highlighted as the most commonly used models.
Hermann (2022)	AI reshapes business strategies and marketing, posing ethical challenges that require multi-stakeholder solutions.
Hong et al. (2022)	This study finds that negative equity market volatility (EMV) shocks generally cause positive oil price shocks, while positive EMV shocks may result in negative oil price shocks.
Hsu et al. (2020)	This research developed an approximate analytical solution for stochastic volatility forward-starting Asian options, offering high accuracy and fast computation times.
Huang and Wu (2018)	This research proposes a deep multiple kernel learning approach for forecasting oil prices, achieving better results and significantly reducing prediction errors compared to traditional models.
Huang et al. (2020)	This study develops a multi-kernel adaptive filter to address the challenge of option price forecasting, providing investors with a better tool to control and hedge their risk in option trading.
Hutchinson et al. (1994)	The authors propose using learning networks for a nonparametric method to estimate derivative pricing formulas, outperforming traditional arbitrage-based methods when the price dynamics of the underlying asset are uncertain.
Johana Marin-Rodriguez et al. (2022)	This study offers a thorough examination of the structure and worldwide patterns of the ever-changing correlation between oil prices and financial assets, from 1982 to 2022, pinpointing prospective zones for more exploration in this area.

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Table 4 – continued from previous page

Reference	Summary
Johnson et al. (2023)	A platform's design boosts competition, consumer surplus, and its earnings through strategic demand-steering rules.
Juda and Parkes (2009)	The paper introduces a model and options-based solution for sequential auctions in e-marketplaces like eBay, coordinating price and winner determination, and making truthful bidding a weakly dominant strategy for buyers.
Kazem et al. (2013)	This paper introduces a forecasting model using chaotic mapping, firefly optimization, and support vector regression to predict stock market prices, addressing their non-linear and non-stationary nature.
King et al. (2005)	This paper presents a model which links investors' liability structures and decision making in a frictionless market to Arbitrage Pricing Theory in order to explain why investors may trade "fairly" even when their beliefs are identical and accurate.
Klein (2021)	Algorithms increasingly set prices, raising concerns about potential collusion and its impact on competition.
Kopalle et al. (2023)	The paper discusses the evolution and impact of dynamic pricing, driven by AI and data analysis, on various industries, highlighting its benefits and challenges.
Kumar et al. (2021)	The importance of the stock market in the economic and social framework of a nation is undisputed, and this article offers an updated overview of the existing research on stock market forecasting using computational intelligent techniques to minimize associated risk.
LeBaron et al. (1999)	This paper presents a simulated stock market where AI algorithms act as traders, replicating many real-world time series and agent behaviors.
Leung et al. (2019)	This paper introduces a novel method using fuzzy association rule mining and fuzzy logic to identify factors affecting pricing decisions and create dynamic pricing strategies for e-commerce products.
Li and Zheng (2024)	A merchant adjusts prices based on new information to maximize expected cumulative revenue efficiently.
Li et al. (2022)	The authors find that by providing ways out of poverty, low-income individuals can increase cooperation and potentially raise whole societies out of economic gridlocks.
Li and Li (2022)	The study finds that AI automation in supply chains can lead to higher profits for retailers, but can negatively impact decentralized supply chains and potentially harm both retailers and suppliers.
Lin (2021)	The study employs AI and ML algorithms to analyze inflation expectation impacts, build central bank disclosure and inflation expectation indices, and examine how China's central bank communication influences inflation expectation formation.
Liu et al. (2014)	The study finds that while the Black-Scholes model holds for zero intelligence traders, the shape of implied volatility smiles is influenced by the collective behavior of traders.
Lo (2021)	The article examines the developments in financial markets over the past 75 years, looking at the impact of theory, practice, regulation, technology, and innovation.
Lunde and Torkar (2020)	This paper uses dynamic factor models and 124 predictors to forecast China's GDP, aiming to improve predictions over univariate autoregression.
Mak (2022)	The paper discusses the potential of operations management to contribute to the smart city movement and suggests promising research directions in energy, transportation, and retail.
Ma et al. (2021)	The authors examine how seller reputation and pricing strategies affect economic interactions and outcomes in online markets.
Makhadmeh et al. (2021)	This study examines the impact of multi-creiterial approach on five different metaheuristic population-based algorithms (GWO-MCA, GA-MCA, PSO-MCA, ALO-MCA, WDO-MCA, and EDE-MCA) on PSPSH (peak shaving problem in smart homes). The findings show that MCA-enabled hybrid approaches delivered superior PSPSH performance compared to the original algorithms.
Marowka et al. (2020)	This paper uses vector auto-regressive models to investigate the soybean crush spread, incorporating time-varying effects and dynamic features from futures price data with a cointegrated time series model.
Martinazzi et al. (2020)	This work explores the link between the Lightning Network (LN) and Bitcoin's market dynamics to assess if LN's efficiency correlates with Bitcoin's market performance.

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Table 4 – continued from previous page

Reference	Summary
Mathieu and Morvan (2019)	This study explores whether rational, determinate behavior can replicate typical financial market traits and if agents with different initial parameters have varying success rates.
Methenitis et al. (2020)	This paper examines how buyers' rationality affects retail markets with identical items, using evolutionary game theory, and finds an optimal rationality level that lowers buyers' costs.
Meylahn and V. den Boer (2022)	This paper investigates whether self-learning algorithms can collude rather than compete and shows that algorithmic collusion is a real threat in markets, facilitated by sharing demand information and using the same pricing algorithm.
Miklós-Thal and Tucker (2019)	The study suggests that improved demand forecasting through AI can disrupt industry collusion, leading to lower prices and increased consumer surplus.
Mirrokni et al. (2020)	The authors propose a system to analyze and demonstrate lower bounds for dynamic mechanisms, preventing sellers from exploiting future distribution information, and investigate the revenue potential of both clairvoyant and non-clairvoyant types.
Mousavi et al. (2014)	A multi-tree genetic programming forest has been created to develop a dynamic portfolio trading system that maximizes returns and minimizes risks, considering transaction costs and technical indices.
Nair and Gupta (2020)	This paper explores AI applications in digital media marketing and offers a guide for social media marketers to enhance their strategies using AI.
Nwogugu (2006)	This article shows that cumulative prospect theory and related models fail to describe decision-making and risk assessment accurately due to their inability to handle multi-criteria factors.
Oliveira (2008)	The authors propose using constraint logic programming to extend Lemke's algorithm for dynamic pricing, improving short- and long-term resource management efficiency.
Park et al. (2004)	This article explores the development of artificial intelligence techniques to enable computational agents to handle increasingly complicated e-commerce decisions, such as bidding in auctions, by employing a more tractable Markov chain model.
Ponta et al. (2012)	This paper presents a simulation of a heterogeneous agent-based market system which produces fat-tailed distributions of returns with a renewal order-generation process that follows a Weibull law.
Rezapour et al. (2017)	This paper explores a company's forward and after-sales supply chains, focusing on uncertainties and imperfect production. It proposes a mathematical model to identify optimal marketing strategies and service levels.
Robu et al. (2013)	The authors propose two truthful allocation mechanisms for dynamic agent populations with non-increasing marginal valuation functions, one of which is more scalable but may be less practical, and demonstrate through a real-world trial of PHEVs in the UK that efficiency is improved compared to a fixed price system.
Shih et al. (2020)	This paper introduces a new bidding approach, EWDQN, for branding campaigns with lifetime and budget limitations. It applies a model-free reinforcement learning model to maximize the number of impressions, based on expected win rate.
Slanina (2008)	This paper explores far-from-equilibrium models of one-dimensional interacting particles to model stock market fluctuations.
Stone et al. (2003)	This article presents a method for developing autonomous bidding agents that bid optimally in multiple auctions using a boosting-based price predictor.
Sunar and Swaminathan (2022)	The paper reviews research on socially relevant issues like energy poverty and inequality, and discusses the role of AI and blockchain in addressing these issues.
Syriopoulos et al. (2021)	This paper proposes a novel and innovative forecasting framework using support vector regression for accurate ship price predictions that outperforms traditional time-series forecasting models.
Tai et al. (2018)	This paper investigates the impact of cognitive ability on market action and outcomes in a double auction context, by examining subjects with varying working memory capacity in two treatments involving veracious and adaptive traders.
Tan et al. (2022)	This paper introduces DeepPricing, a data-driven model for valuing Convertible Bonds using novel financial time-series generative adversarial networks to capture stock return dynamics and preserve real-world bond specifications.

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Table 4 – continued from previous page

Reference	Summary
Tian et al. (2022)	This paper presents a novel method for predicting stock prices by leveraging co-movement among individual firms' stock prices through dynamic stock graph construction and hybrid-attention dynamic graph neural network inductive graph representation learning.
Tsao et al. (2021)	This study examines dynamic discounting in supply chain design, using discounted cash flows to maximize total profit's present value.
Tuncay et al. (2024)	The study proposes a reinforcement learning model for dynamic hotel pricing that addresses the cold start problem, optimizes profit and demand, and outperforms other models in tests.
Wah et al. (2017)	The authors study market making impacts, finding that market makers boost total welfare and investor surplus in thin markets and when traders are impatient.
Wang and Shao (2021)	This paper examines how cooperation contracts between one manufacturer and one supplier of a closed-loop supply chain can affect their capacity investment, pricing, and collecting channels decisions.
Wang et al. (2018)	This paper introduces the DIN-AI model, a hybrid method combining a data fluctuation network with AI algorithms to enhance crude oil price forecasting.
Xue et al. (2017)	This article presents a study of optimal joint pricing and dynamic product quality investment strategies under the existence of quality inflation and consumers' reference quality effect, with a focus on the differences between the strategies of finite and infinite planning horizons.
Yamamoto (2022)	This study uses a unique Tokyo Stock Exchange dataset to identify investor predictors and their price impact, validating several agent-based models for financial market features.
Yang and Mehmed (2019)	This paper examines the use of forward freight agreements to improve freight rate forecast accuracy using two artificial neural network models (NARNET and NARXNET).
Yang et al. (2022)	This work integrates dynamic pricing, information disclosure, and deep reinforcement learning to help retailers reduce food waste and maximize profits in fresh produce sales.
Ye et al. (2021)	This paper examines the complex problem of designing auction parameters for online industrial auctions, with the goal of improving the performance of auctions by combining expert knowledge with insights learned from data.
Yeh (2008)	The influence of traders' intelligence on market performance depends on the characteristics of their learning styles, with intelligence helping to improve market performance.
Yeh and Yang (2010)	This paper suggests a framework based on agents to investigate how restrictions on prices affect volatility, price distortion, volume, liquidity, and welfare in an artificial stock market comprising boundedly rational and different traders.
Yeh and Yang (2013)	This paper studies price limits in an artificial stock market with bounded-rational and diverse traders, finding delayed price discovery and trading interference but no volatility spillover.
Yu and Chen (2018)	An agent-based model examines herding effects on a double auction market's order book, revealing that herding decreases price return, spread, and volatility autocorrelation time.
Yuan et al. (2021)	This study develops an AI-based emissions permit trading system to reduce risk and ensure the stability of trading platforms for transportation firms by exploiting a new mathematical property and demonstrating an optimal trading policy.
Zhang et al. (2019)	This study suggests a combination of dynamic fluctuation network (DFN) and artificial intelligence (AI) to predict the Baltic Dry Index (BDI), proving to be more precise than AI-only-based models.
Zhu et al. (2021)	This research explores optimal pairs trading strategies with symmetric and asymmetric limits, using data from China's securities market to empirically measure their effectiveness.

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