

Research Article

From Rational Price to Algorithmic Rationality: Behavioral Transformation in Artificial Intelligence–Driven Pricing

Rasyonel Fiyattan Algoritmik Rasyonaliteye: Yapay Zekâ Destekli Fiyatlandırmada Davranışsal Dönüşüm

Ahmet KASAP Assoc. Prof. Dr., Tokat Gaziosmanpaşa University Turhal Faculty of Applied Sciences ahmet.kasap@gop.edu.tr https://orcid.org/0000-0001-7231-2693	Mustafa KARAKUŞ Assoc. Prof. Dr., Ankara Hacı Bayram Veli University Faculty of Financial Sciences mustafa-karakus@hbv.edu.tr https://orcid.org/0000-0001-7207-6686
Feyzullah TECİRLİ Dr., Mersin University Anamur Vocational School feyzullah.tecirli@mersin.edu.tr https://orcid.org/0000-0002-3565-7905	Çınar KAYA Dr., Tokat Gaziosmanpaşa University Turhal Faculty of Applied Sciences cinar.kaya@gop.edu.tr https://orcid.org/0009-0007-7268-2943

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Öz

Yapay zekâ temelli ekonomilerin güncel aşamasında fiyatlandırma, artık yalnızca klasik iktisadi rasyonalite sınırları içinde işlememekte, bunun yerine giderek davranışsal ve algoritmik bir yapıya evrilmektedir. Dijitalleşmenin, otomasyonun ve veri odaklı karar sistemlerinin hız kazanmasıyla birlikte fiyat oluşumu, basit bir arz–talep dengesinin ötesine geçmiş ve tüketici psikolojisi, etik kaygılar ve algoritmik yönetim mekanizmalarıyla iç içe geçmiş çok boyutlu bir sürece dönüşmüştür. Bu kavramsal çerçevede çalışma, yapay zekâ temelli fiyatlandırma modellerinin tüketici davranışları, algılanan fiyat adaleti, güven düzeyi ve rekabetin niteliği üzerindeki etkilerini kuramsal bir yaklaşım ve kapsamlı bir literatür incelemesi yoluyla ele almaktadır. Elde edilen bulgular, algoritmik fiyatlandırmanın gelir maksimizasyonu ve piyasa etkinliği açısından önemli katkılar sunduğunu, ancak aynı zamanda şeffaflık eksikliği, veri gizliliği sorunları ve yetersiz etik denetim nedeniyle toplumsal refah açısından yeni kırılma noktaları da yarattığını göstermektedir. Bu çerçevede dijital ekonomilerin sürdürülebilir geleceği, yalnızca etkinlik artışlarına değil, aynı zamanda hesap verebilirlik, etik duyarlılık ve insan merkezli yönetim ilkeleri üzerine inşa edilen fiyatlandırma sistemlerinin geliştirilmesine bağlıdır.

Anahtar Kelimeler: Yapay Zekâ; Algoritmik Fiyatlandırma; Davranışsal İktisat; Fiyat Adaleti; Etik Yönetişim

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Abstract

In the contemporary phase of artificial intelligence-driven economies, pricing no longer operates strictly within the boundaries of classical economic rationality, evolving instead toward a behavioral and algorithmic structure. With the acceleration of digitalization, automation, and data-based decision systems, price formation has moved beyond a simple supply-demand balance and has become embedded in consumer psychology, ethical considerations, and algorithmic control mechanisms. Within this conceptual framework, the present study examines how AI-based pricing models influence consumer behavior, perceived price fairness, trust, and the nature of competition, drawing on theoretical perspectives and an extensive review of the literature. The analysis reveals that although algorithmic pricing contributes to revenue maximization and improved market efficiency, it also introduces social and institutional risks arising from limited transparency, data privacy concerns, and insufficient ethical governance. From this perspective, the long-term viability of digital markets relies not merely on efficiency gains, but on the development of pricing architectures that are accountable, ethically informed, and oriented toward human-centered governance.

Keywords: Artificial Intelligence; Algorithmic Pricing; Behavioral Economics; Price Fairness; Ethical Governance

1. Introduction

Across the global economy, digitalization, automation, and data-driven decision systems are reshaping how markets function. At the core of this transformation stands Artificial Intelligence (AI), a technology that is changing how firms produce and manage, and just as much how markets behave and how prices are formed. Kaplan and Haenlein (2019) describe AI as systems that can interpret data, learn from it, and apply this knowledge flexibly to achieve predefined goals, noting that its capabilities continue to expand rapidly. Viewed from this angle, AI is no longer simply a supportive tool but has become a strategic force capable of influencing the structure of global competition. As economic activity increasingly moves onto digital platforms, algorithms that track consumer behavior in real time and adjust prices dynamically have begun to replace traditional pricing logics.

For much of the twentieth century, price theory was dominated by the neoclassical assumption of rational decision-makers. In this framework, Varian (2010) characterizes price as a signaling device that coordinates supply and demand: consumers aim to maximize utility, while firms seek to maximize profit by minimizing costs. Yet over the last two decades, behavioral economics has shown that this neat rationality assumption often fails in practice. Kahneman (2011) demonstrates that human choices are frequently guided by what he terms “fast and intuitive” System-1 thinking, meaning that price responses are strongly shaped by emotions and cognitive shortcuts rather than strict calculation. These insights imply that effective pricing cannot rely on mathematical optimization alone but must also incorporate psychological dynamics.

This realization has given rise to behavioral pricing, which links economic theory with consumer psychology. According to Nunan and Di Domenico (2022), variables such as trust, perceived fairness, and ethical expectations significantly influence how consumers react to prices. Similarly, data-driven personalized pricing in digital marketing environments is increasingly understood to be transforming the nature of consumer loyalty. Whereas conventional pricing models focus mainly on costs and competitive pressures, behavioral pricing assigns equal importance to perception, emotion, and cognitive bias. In this setting, price becomes more than a numerical outcome. It turns into a mechanism for shaping how consumers interpret value.

The expansion of AI technologies has accelerated this behavioral shift. By processing large volumes of consumer data, AI systems can estimate purchasing intentions, willingness to pay, and price sensitivity, allowing pricing decisions to be generated by algorithms rather than by human judgment. This development can be understood as a form of algorithmic rationality: as Asker, Fershtman, and Pakes (2021) show, learning-based pricing algorithms build their own internal decision rules within markets. In doing so, they challenge the traditional image of a rational agent moving toward equilibrium and

instead create a market structure defined by continuous human–machine interaction. Kaplan and Haenlein (2020), using the PESTEL framework, further note that AI reshapes productivity as much as the ethical and governance dimensions of economic systems.

Although a substantial body of research addresses either behavioral pricing or algorithmic pricing separately, few studies bring these two literatures into a single explanatory framework. Studies on behavioral economics, such as Kahneman (2011) and Nunan and Di Domenico (2022), primarily focus on how consumers perceive and respond to prices, without examining the technological mechanisms that generate those prices in the first place. Conversely, studies on algorithmic pricing, including Asker, Fershtman, and Pakes (2021), concentrate on the technical and competitive dynamics of AI-driven systems, paying comparatively little attention to how these systems reshape consumer psychology, trust, and perceived fairness. This separation leaves a gap in understanding how algorithmic decision-making and behavioral responses interact as a single, co-evolving system. The present study addresses this gap by developing an integrated theoretical account, one that treats algorithmic rationality and behavioral pricing not as parallel developments but as mutually reinforcing dimensions of a single transformation in how prices are formed and experienced.

Against this background, the central purpose of this study is to connect behavioral pricing with the dynamics of the AI era, highlighting the tension between economic rationality and consumer psychology. The analysis treats price not merely as a market signal but as a data-driven behavioral stimulus. Accordingly, it investigates how AI-based pricing strategies affect consumer decision-making, reshape perceptions of fairness and trust, and depart from the predictions of classical economic theory.

As AI becomes embedded in pricing processes, the notion of equilibrium in economics is increasingly replaced by feedback-driven learning loops. Instead of reflecting a stable balance between costs and demand, prices are now continuously adjusted by algorithms that anticipate how consumers will react. This shift requires classical microeconomic theory to be reconsidered and human decision-making to be reinterpreted in the context of digital environments. Understanding behavioral pricing under AI therefore demands a framework that integrates economic logic with psychological and algorithmic dimensions of consumer behavior.

The aim of this paper is to build such a theoretical framework by linking the behavioral pricing literature with the evolution of AI technologies. Its focus is restricted to the effects of AI-based pricing systems on consumer behavior, leaving aside firm performance, competition law, and macroeconomic policy issues. Even so, the results are intended to be relevant both for academic research and for applied marketing practice. In this way, the study clarifies how pricing has shifted from classical rational models toward cognitively driven structures in the digital age, showing that AI represents a technological development and, just as much, a new behavioral and ethical paradigm in modern economics.

The remainder of this paper is organized as follows. Section 2 lays out the conceptual foundations of pricing, tracing the shift from neoclassical assumptions to behavioral accounts of consumer decision-making. Section 3 develops the theoretical framework of AI-based pricing and algorithmic rationality. Section 4 reviews the empirical and conceptual literature on AI-driven pricing across different industries and regulatory contexts. Section 5 examines the behavioral dimension of AI-based pricing in more detail, while Section 6 discusses the interaction between economic rationality and psychological responses under conditions of information asymmetry. Section 7 considers the ethical and governance implications of this new pricing paradigm, and Section 8 concludes with a discussion of the study's contributions, limitations, and directions for future research.

2. Conceptual Foundations

2.1. Economic Foundations of Pricing

Within economic theory, pricing has always occupied a pivotal position, serving as one of the primary mechanisms through which markets coordinate economic activity. In classical frameworks, price

functions as a central signal that guides both producers and consumers in their decision-making. Varian (2010) characterizes price as the instrument through which resources are allocated and supply is brought into balance with demand. Under this logic, market participants behave as rational agents: firms seek to maximize profits, while consumers attempt to obtain the greatest possible satisfaction within their budgetary limits. The price that emerges, therefore, reflects the combined outcome of individual choices aggregated across the market.

Neoclassical theory further assumes that such interactions naturally move the market toward equilibrium. Through the operation of the so-called “invisible hand,” coordination is achieved without the need for direct external control. Yet this stylized model offers only a partial account of how real markets operate. In practice, rationality is constrained by imperfect information, uncertainty, and cognitive limitations, which weaken the explanatory power of the purely rational framework. Even so, the coordinating function of price within the economic system remains undeniable.

In the era of artificial intelligence, however, this classical interpretation of equilibrium is being reshaped. Technological progress has altered the way prices are formed: rather than arising solely from interactions among market participants, prices increasingly emerge from data-driven decision systems. Algorithms now process consumer behavior in real time and generate dynamic prices, shifting the task of market coordination from human judgment to machine learning processes. In this context, price no longer merely reflects market exchange but also embodies the flow of digital information.

As AI becomes embedded in economic activity, the very notion of rationality, and with it the meaning of price, undergoes a fundamental shift. Whereas classical theory links price to production costs and demand schedules, digital markets rely on consumer preferences, historical purchasing patterns, and predictive analytics. Price, under these conditions, operates as a form of data-based expectation about future behavior. It is therefore not only the outcome of supply–demand interaction but also the strategic product of algorithmic calculation.

This evolution calls into question one of the core assumptions of traditional economics: the idea that humans alone determine market outcomes through rational choice. Today, pricing decisions increasingly originate from systems that learn, process vast datasets, and generate predictions. As a result, although classical economic principles still provide the foundation for understanding price, their scope and meaning have been fundamentally redefined in AI-driven markets.

2.2. Behavioral Economics and Consumer Decision-Making Processes

Traditional economic theory is built on the premise that consumers are rational, fully informed, and consistently motivated to maximize utility. In practice, however, this assumption rarely reflects how people actually make decisions. Behavioral economics emerged precisely to address this discrepancy by combining insights from psychology, neuroscience, and sociology to explain how economic behavior is influenced by emotions, cognition, and social context. Kahneman (2011) distinguishes between two modes of thinking that govern decision-making: System 1, which is fast, intuitive, and emotionally driven, and System 2, which operates more slowly through deliberate and analytical reasoning. This dual-system framework reveals that price perceptions are not shaped by calculation alone but are deeply affected by psychological processes.

From this perspective, price is not simply a piece of information about market conditions but also conveys meanings related to value, quality, and trust. Consumers frequently interpret prices through reference points, such as earlier prices or advertised discounts, which can alter perceived value through framing effects. In digital marketing environments more broadly, behavioral economics has fundamentally altered how consumers respond to prices: data-based personalized pricing influences loyalty, while ongoing price adjustments significantly affect how much consumers trust a firm. Rather than evaluating prices through purely rational comparison, individuals rely heavily on memory, perceived fairness, and accumulated trust.

The ethical implications of this process are emphasized by Nunan and Di Domenico (2022), who analyze how price differentiation in digital platforms shapes consumer confidence. When personal data are used to tailor prices, the line between customized offerings and discriminatory practices becomes increasingly blurred. Algorithmic systems that determine individualized prices based on behavioral data have, as a result, revived long-standing concerns about fairness in pricing. In this way, behavioral economics extends beyond individual decision-making to examine how these practices reshape market structures and corporate strategies.

A central insight of behavioral economics is that irrationality in consumer behavior is not random but systematic. As Kahneman (2011) explains, people make predictable judgment errors, particularly in situations involving uncertainty and risk, where intuitive responses tend to dominate. This implies that effective pricing strategies must be designed around optimization models as much as around psychological balance. Today, firms increasingly rely on AI to detect these cognitive patterns and to build predictive systems that anticipate purchasing behavior.

Under these conditions, price takes on the role of a cognitive trigger rather than remaining a purely economic indicator. When deciding whether to buy, consumers weigh emotional satisfaction, trust, and perceived fairness alongside income and utility. This shift represents one of the most important contributions of behavioral economics to price theory. Consequently, price formation is now influenced by supply and demand, and in equal measure, by the perceptual and emotional mechanisms of the human mind (Kahneman, 2011).

2.3. Consumer Psychology and Perceived Price Fairness

To understand how consumers respond to prices, psychological mechanisms are just as important as formal economic models. A price does not function merely as a numerical exchange rate but also embodies how individuals interpret value, trust, and fairness. Behavioral research has repeatedly shown that reactions to prices are often guided less by calculation and more by cognitive shortcuts and emotional responses. Kahneman (2011) explains that intuitive, experience-based judgments play a central role in shaping how prices are perceived. For this reason, a price increase is rarely interpreted as a neutral economic adjustment. It is frequently experienced as a violation of fairness.

Digital environments further amplify these psychological dynamics. Weinmann, Schneider, and vom Brocke (2016) describe online platforms as “choice architectures” that subtly influence decisions through their design. Small features, such as a message stating that only a few items remain in stock, can trigger fear of missing out and push consumers toward quicker purchases. These nudging mechanisms reinforce the behavioral foundations of modern pricing, while also introducing new ethical dilemmas. Nunan and Di Domenico (2022) show that perceptions of price fairness are among the strongest drivers of trust and loyalty in digital markets. Although personalized pricing may generate short-term gains, offering different prices to similar consumers weakens the sense of fairness and ultimately damages trust.

Loss aversion is another crucial psychological factor shaping how prices are evaluated. As Kahneman (2011) points out, consumers react more strongly to price increases than to equivalent reductions, which makes the emotional framing of prices particularly important. The nudging principles identified by Weinmann et al. (2016) further indicate that consumer decisions depend not only on the numerical differences between options but also on the context in which a choice is presented. Araf, Hoque, Chowdhury, Rahman, and Alam (2024) add that perceived fairness stands at the center of ethical debates surrounding AI-based pricing. Although algorithmic systems appear neutral, biases embedded in data can systematically disadvantage certain groups. In this sense, fairness in pricing is not merely an economic issue. It is also tied to social justice and ethical accountability.

When these psychological mechanisms, cognitive biases, and fairness perceptions are viewed together, price emerges as a deeply layered construct in contemporary markets. It no longer operates simply as a tool of exchange but as a form of communication that shapes beliefs, moral sensitivity, and trust. For

this reason, effective pricing in the AI era must go beyond optimization models and take into account the psychological coherence of consumer behavior (Kahneman, 2011; Weinmann et al., 2016; Nunan & Di Domenico, 2022, p. 453).

Together, behavioral economics and consumer psychology make clear that price is not a purely rational signal but a construct molded by perception, bias, and ethical judgment. As digitalization accelerates and AI-driven decision systems spread, a new challenge emerges: translating these human-centered dynamics into algorithmic processes. Prices are now shaped by supply and demand, and just as much by data-based learning models and automated decision rules. In this evolving landscape, the meaning of rationality itself is being redefined, laying the conceptual groundwork for an economy increasingly governed by algorithmic logic.

3. Theoretical Framework

3.1. AI-Based Pricing Models

The incorporation of artificial intelligence into economic decision-making has fundamentally altered how prices are formed. Whereas traditional pricing relied on historical cost structures, demand projections, and competitor behavior, AI-driven systems draw on constantly refreshed, multidimensional data streams to determine prices that vary by customer, product, and moment in time. What sets these systems apart, as Pillai (2023) notes, is their capacity for real-time learning. By applying machine-learning techniques, AI continuously monitors consumer responses and repeatedly updates its estimates of demand elasticity. As a result, pricing shifts away from backward-looking evaluation toward forward-looking prediction.

This transformation is clearly illustrated by Kristiansson's (2023) application of Double Machine Learning (DML) within the insurance sector. The DML framework is designed to uncover causal relationships among the variables that influence pricing decisions, which allows it to reduce bias and improve the accuracy of price elasticity estimates. Unlike conventional statistical approaches such as GLM or GAM that rely mainly on correlations, this method isolates the causal effect of price on the probability of purchase. Applied to a large dataset of insurance offers and sales, the approach estimates individual price elasticities and groups them by customer segment to inform small market-based adjustments layered on top of the existing risk premium. As a result, firms are able to fine-tune price sensitivity while simultaneously improving revenue outcomes (Kristiansson, 2023).

Zhao, Jiang, and Yu (2025) extend this logic through the concept of contextual dynamic pricing, in which AI functions not only as an analytical tool but also as an adaptive decision-maker. Their model integrates consumer-level information with external conditions such as economic trends, competitive pressure, and behavioral histories. A key innovation in their approach is the use of a local differential privacy algorithm, which permits individualized price optimization while protecting data privacy. This enables highly accurate price forecasts without compromising legal or ethical standards, allowing AI-based systems to improve both performance and compliance (Zhao et al., 2025, p. 6).

What ultimately distinguishes AI-driven pricing is its capacity for continuous learning. By observing how markets and consumers respond, these systems constantly refine their pricing strategies. Traditional pricing schemes, by contrast, rely on periodically updated but essentially static rules. Pillai (2023) describes AI-driven dynamic pricing as a paradigm shift away from static pricing methods, in which machine learning and real-time data analysis allow prices to be continuously recalculated in response to new information. In this setting, price ceases to be a fixed parameter and instead becomes a flexible decision variable that reacts instantly to environmental signals.

From the standpoint of behavioral pricing, the most important feature of these models is their ability to combine economic and psychological factors at the level of the individual consumer. AI algorithms draw on purchase histories, brand attachment, and willingness to pay in order to construct personalized interpretations of value. Price, in this sense, reflects the objective attributes of a product, and just as

much, how each consumer cognitively frames its worth. Although such precision creates the risk of manipulation, when applied responsibly it can enhance efficiency for both buyers and sellers.

Taken together, AI-based pricing systems give rise to a new form of market coordination that can be described as a “learning equilibrium.” Unlike classical equilibrium, which emerges from supply and demand alone, this dynamic is shaped by information flows and behavioral feedback. Price thus becomes more than an economic indicator. It operates as a data-driven behavioral mechanism at the core of decision-making in the AI economy (Pillai, 2023, p. 100; Zhao et al., 2025, p. 8).

3.2. Algorithmic Rationality: The Transformation of Decision-Making

The spread of AI-based pricing systems has forced economists to rethink one of the discipline’s most fundamental concepts: rationality. In classical theory, rational behavior refers to the ability of individuals to make deliberate choices in order to maximize their own interests. In algorithm-driven markets, however, rationality is no longer defined primarily by human judgment but by computational capacity, data responsiveness, and learning ability. This shift can be described as algorithmic rationality, a form of decision-making that originates in human logic yet ultimately goes beyond it. Algorithms of the kind studied by Asker, Fershtman, and Pakes (2021) track market conditions, register how prices are received, learn from these reactions, and use that information to guide future actions. Under such conditions, market outcomes are increasingly produced by machine-based optimization rather than by human cognition.

Rather than abandoning rational choice theory, algorithmic rationality expands it. Human decision-making is constrained by limited attention, emotions, and cognitive biases, whereas algorithmic systems can operate with greater internal consistency and far larger volumes of data. Brown and MacKay (2021) examine this issue empirically, showing that firms with faster pricing technology can commit to reacting to rivals’ prices, which softens price competition and raises average prices even in the complete absence of any collusive intent. Thus, while algorithmic rationality improves computational efficiency, it simultaneously creates new forms of market risk.

Within this framework, rationality is no longer best understood as a psychological trait but as a computational process. This shift carries a paradox of its own: although AI models generate highly accurate outcomes, their internal reasoning often remains hidden from external observers, reflecting what Spann et al. (2024) describe as the “black-boxyness” of algorithmic pricing systems. Rationality, therefore, becomes less a clearly observable benchmark of efficiency and more a probabilistic feature of evolving systems. Unlike the classical rational agent, which is evaluated by its outcomes, algorithmic rationality is defined by how decisions are produced and updated over time.

Asker et al. (2021) further show that this new form of rationality introduces adaptive learning into the process by which algorithms arrive at their pricing strategies. Traditional economic models assume that once equilibrium is reached, it remains stable. Algorithmic systems reach a comparably stable outcome, yet the level at which they settle depends on how they learn: synchronous learning converges toward competitive, Nash-level pricing, whereas asynchronous learning tends to settle well above competitive levels (Asker et al., 2021). The result is an environment in which the path toward equilibrium, rather than the notion of equilibrium itself, requires an adaptive theoretical lens. In this sense, algorithmic rationality represents not merely a technological feature but an entirely new mode of economic reasoning.

These developments also intersect with behavioral pricing research. While algorithms are designed to correct for the biases and limits of human decision-making, they are trained on data generated by human behavior. As a result, they can inherit, and even intensify, the same distortions present in those data. Despite their analytical power, algorithmic systems may reproduce patterns of irrationality embedded in the information they process. Araf, Hoque, Chowdhury, Rahman, and Alam (2024) raise a related concern, observing that pricing algorithms learned from consumer behavior patterns, such as those used

on ridehailing platforms, can come to reflect the demographic composition of neighborhoods and produce discriminatory pricing outcomes even without explicit intent to discriminate.

Algorithmic rationality thus marks a shift from human-centered to machine-centered decision structures. Rationality is no longer solely a mental capacity but has become an adaptive property of data-driven systems that respond to rapidly changing market signals through autonomous learning. This transformation offers the promise of greater efficiency while also raising profound ethical concerns. By reshaping how decisions are made, how equilibrium is defined, and how fairness is understood, AI has fundamentally altered the meaning of rationality in economic life (Asker et al., 2021; Spann et al., 2024).

Taken together, Sections 3.1 and 3.2 outline a conceptual sequence that connects three levels of analysis: the technical mechanisms of AI-based pricing models, the redefinition of rationality as a computational rather than purely human process, and the behavioral and ethical consequences that follow from this shift. AI-based pricing models, discussed in Section 3.1, supply the technical infrastructure through which prices are continuously learned and updated. Algorithmic rationality, discussed in Section 3.2, describes the resulting change in how market decisions are made and justified. Read together, these two dimensions form the theoretical backbone of the present study, linking the economic logic of price formation to the behavioral and psychological consequences examined in the sections that follow.

4. Literature Review

The literature review presented in this section follows a traditional, narrative approach rather than a systematic protocol such as PRISMA. Studies were selected on the basis of their conceptual and thematic relevance to AI-based pricing, behavioral economics, and algorithmic decision-making, drawing on peer-reviewed journal articles, conference proceedings, working papers, and theses published primarily between 2016 and 2025. This approach allows the review to integrate conceptual, empirical, and regulatory perspectives into a single thematic discussion, although it does not follow the formal inclusion and exclusion criteria characteristic of systematic reviews.

The growing use of artificial intelligence in pricing has brought about a deep shift in how economic decisions are made. According to Nunan and Di Domenico (2022), pricing authority has gradually moved away from managerial judgment toward algorithmic selection, a development that has intensified ethical debates surrounding consumer autonomy and price fairness. Along similar lines, Adams, Fang, Liu, and Wang (2025) document that the adoption of AI-based pricing among firms has grown substantially over the past decade, showing that adopting firms tend to experience faster growth in sales, employment, and markups. Brown and MacKay (2021) further show that asymmetries in pricing frequency and short-run commitment can support prices above the competitive level even when firms do not engage in anything resembling explicit collusion.

Empirical research on the technical foundations of this transformation shows that machine-learning models consistently outperform traditional methods in predicting prices. Das et al. (2024) report that Gradient Boosting achieves forecasting accuracy of 94%, while Kurniati and Sulistiwaty (2023) demonstrate that artificial neural networks reach 87% accuracy, making them particularly useful for small firms. In a similar vein, Namlı, Ünlü, and Gül (2019) find that support vector machines provide the most reliable predictions in second-hand automobile markets. Peniaha (2025) reinforces these conclusions by applying random forest and XGBoost techniques to transport auctions, where the models explain 89% of price variation, confirming the strong practical value of AI for price optimization.

Taken together, however, these accuracy metrics say little about how such systems affect consumer trust or perceived fairness. High predictive accuracy is treated as an end in itself, with success measured almost exclusively in terms of forecasting error or revenue improvement rather than in terms of how consumers experience or evaluate the resulting prices. This narrow focus on technical performance leaves an important explanatory gap, one that the present study seeks to address by linking algorithmic accuracy to the behavioral and psychological outcomes examined in later sections.

Research on learning-based algorithms further indicates that adaptive and contextual approaches improve pricing performance. Ganti et al. (2018) show that an active-learning version of Thompson Sampling generates higher revenues than conventional strategies. Zhao, Jiang, and Yu (2025) extend this line of work by proposing a contextual pricing model based on local differential privacy, enabling firms to protect consumer data while still optimizing revenue. Within insurance markets, Kristiansson (2023) applies Double Machine Learning to estimate price elasticity and demonstrates that segment-specific models, when aligned with loss ratios, can be operationally effective, while also drawing attention to the ethical risks that price optimization can pose if applied without regard for fairness.

AI-driven dynamic pricing has also been applied across a wide range of industries. Al Sulaie (2025) finds that insurance premiums become more accurate and personalized when real-time risk data are incorporated into AI-based pricing algorithms within fintech ecosystems. In e-commerce, Almahadeen et al. (2025) apply Gradient Boosting Machines to historical transaction data to model dynamic pricing, reporting a high R^2 of 0.92, which underscores the practical value of ensemble learning methods for revenue-oriented pricing decisions. Hernandez et al. (2024) use genetic algorithms to optimize upgrade pricing for configurable products, illustrating how AI can guide product-level pricing strategies. Thota et al. (2024) likewise combine K-means customer segmentation with regression-based dynamic pricing for e-commerce data, showing that clustering customers before setting prices can support more targeted, personalized pricing strategies. Ariyaratna et al. (2024) present a related integrated AI service for small and medium-sized e-commerce enterprises that combines dynamic pricing with personalized recommendations and promotional automation, while stressing the importance of robust customer data security in such systems.

While these industry-specific findings confirm the commercial value of AI-driven pricing, they generally treat consumer response as a performance metric rather than as a behavioral or psychological phenomenon in its own right. Revenue gains, forecasting accuracy, and adoption rates are reported as evidence of success, yet these indicators say little about whether consumers perceive the resulting prices as fair or trustworthy. As a result, the sectoral literature demonstrates that AI-based pricing works in a narrow technical sense, without clarifying how it is experienced by the people who ultimately pay these prices.

At the same time, research on consumer behavior reveals growing concerns about fairness and ethical trust in algorithmic pricing. Seele, Dierksmeier, Hofstetter, and Schultz (2021) note that when the personalized dimension of algorithmic pricing is disclosed to consumers, it tends to be perceived as unfair or manipulative, which can in turn reduce their trust in the practice. İbiş (2024) observes that while AI-based pricing improves efficiency in the food and beverage sector, rapid price adjustments can weaken perceptions of fairness and trust. Yılmazel (2024) similarly reviews how AI-supported marketing tools operate across mechanical, cognitive, and emotional dimensions, with dynamic pricing forming one part of this broader shift.

These behavioral findings, although valuable, are rarely connected back to the specific algorithmic mechanisms discussed in the technical literature. Studies in this stream tend to describe consumer reactions to pricing outcomes without examining how particular design choices, such as the type of learning algorithm or the granularity of personalization, actually produce those reactions. This leaves the link between system design and consumer perception comparatively underexplored, and it is precisely this link that the theoretical framework developed in this study attempts to make explicit.

The regulatory and ethical dimensions of algorithmic pricing have accordingly attracted increasing attention. Li (2022) argues that the GDPR does not adequately cover affinity-based pricing and calls for new legal protections grounded in group privacy. Evas (2020) suggests that ethical AI policies in Europe can support economic growth, while Kaplan and Haenlein (2020) advocate a broader framework of human-centered AI governance that encompasses ethics, employment, and education. Spann et al. (2024) warn that although algorithmic pricing improves efficiency, it also increases the risk of tacit cartelization, making stronger regulatory oversight essential.

Collectively, these regulatory contributions identify important governance challenges but stop short of proposing an integrated framework that connects specific algorithmic design choices to the behavioral and ethical outcomes they are meant to prevent. Most proposals call for greater transparency or stronger oversight in general terms, without specifying which technical features of pricing algorithms are most likely to produce discriminatory or manipulative outcomes. Bridging this gap would require regulatory research to engage more directly with the technical literature reviewed earlier in this section, rather than treating governance and algorithm design as separate concerns.

From a behavioral perspective, these risks highlight the importance of design choices in digital environments. Weinmann, Schneider, and vom Brocke (2016) introduce the concept of digital nudging, showing how interface design can subconsciously influence price-related decisions. Asker, Fershtman, and Pakes (2021) further demonstrate that different learning regimes can produce very different competitive outcomes, ranging from Nash equilibria under synchronous learning to monopoly-like pricing under asynchronous learning. Together, these findings make clear that algorithmic pricing raises issues of governance as much as it does technical efficiency.

Sustainability and social responsibility have also entered this debate. Drawing on a synthesis of 48 studies, Araf et al. (2024) argue that AI-based pricing must balance economic efficiency with social equity and environmental sustainability. Oteri et al. (2023) similarly note that the tension between profit maximization and data ethics is becoming a central concern in corporate strategy.

Sustainability-oriented studies of this kind, however, tend to remain at a conceptual level, offering broad normative principles rather than a framework for analyzing how such principles interact with the behavioral dynamics identified elsewhere in the literature. Concepts such as economic, social, and environmental sustainability are proposed as desirable goals, but the mechanisms through which they might be operationalized in actual pricing algorithms are seldom specified. This conceptual gap further motivates the integrated approach developed in the present study, which treats efficiency, fairness, and trust as interdependent rather than as separately pursued objectives.

Finally, work that integrates behavioral and technological perspectives has re-centered human cognition in pricing research. Kumari and Kumar (2024) provide a broad review of dynamic pricing trends across industries, situating algorithmic and AI-driven pricing strategies alongside recurring concerns about fairness and transparency in pricing decisions. Kuruca, Üstüner, and Şimşek (2022) show that AI-driven chatbots play a pivotal role in personalization and customer experience management in digital marketing. Related work also indicates that AI-based pricing for tokenized assets has the potential to increase both transparency and market stability.

Taken together, this body of work demonstrates that AI-based pricing has been studied extensively from technical, sectoral, behavioral, and regulatory angles, yet these strands remain largely disconnected from one another. Technical studies emphasize predictive accuracy and revenue outcomes without addressing how consumers interpret or trust the resulting prices, while behavioral and ethical studies rarely engage with the algorithmic mechanisms that produce these effects in the first place. The present study differs from this fragmented literature by explicitly connecting algorithmic rationality with behavioral pricing theory, treating consumer trust, fairness perceptions, and market efficiency as interdependent outcomes of the same underlying process rather than as separate research agendas.

5. The Behavioral Dimension of AI-Based Pricing

5.1. Dynamic and Personalized Pricing

The widespread adoption of AI in pricing has made fixed prices largely obsolete, replacing them with systems that treat price as a continuously adjustable decision variable. By monitoring both market conditions and consumer behavior in real time, these systems are able to optimize revenue while also strengthening competitive positioning and the overall customer experience (Pillai, 2023, p. 101). In digital retail environments, algorithms draw on browsing histories and past purchases to generate

individualized prices. Yet as personalization becomes more refined, maintaining consumer perceptions of fairness and trust becomes increasingly difficult (Valldosera Grifoll, 2025, p. 13).

This form of individualized pricing raises substantial ethical concerns. When similar consumers are charged different prices and the logic behind those differences is not transparent, the sense of fairness is easily undermined. For this reason, sustainable digital markets require pricing systems that are guided not only by economic efficiency but also by ethical standards that protect consumer confidence (Nunan & Di Domenico, 2022, p. 457).

Because AI systems continuously learn from user behavior, price itself begins to function as a psychological signal. Messages such as “only a few items left” or “several people are viewing this product” activate perceptions of scarcity and push consumers toward faster decisions (Weinmann, Schneider, & vom Brocke, 2016, p. 435). In this way, price moves beyond its traditional economic role and becomes a tool for cognitive guidance. To prevent misuse and preserve competitive legitimacy, principles of transparency and accountability must therefore be built into AI-based pricing frameworks (Valldosera Grifoll, 2025, p. 26).

5.2. Integration of Behavioral Data into Pricing Strategies

In data-driven marketing environments, pricing is no longer shaped solely by costs and demand curves but by continuous streams of consumer behavior. Every digital trace, whether a search query, a click, or an item added to a cart, provides information that can be used to guide pricing decisions. When processed effectively, these signals allow firms to refine demand forecasts and implement highly personalized pricing strategies (Valldosera Grifoll, 2025, p. 21). By linking pricing with customer lifecycle management, AI-based analytics convert price from a simple economic indicator into a knowledge-based tool that can interpret, anticipate, and even influence consumer behavior (Kurniati & Sulistiawaty, 2023, p. 85).

At the same time, embedding behavioral data into pricing models raises serious concerns about privacy and ethics. Data that consumers share, often unknowingly, can become the basis for differential pricing, blurring the boundary between personalization and the right to privacy (Nunan & Di Domenico, 2022, p. 459). If algorithmic systems operate without transparency or accountability, they may create the impression of manipulation, ultimately weakening consumer confidence. For this reason, the long-term future of AI-based pricing depends on technical accuracy and, equally, on ethical, human-centered system design (Ariyaratna et al., 2024, p. 49).

How consumers perceive prices extends far beyond their monetary value. Price communicates signals about quality, reliability, and brand reputation, making it a central element of trust in digital markets (Dodds et al., 1991, as cited in Nunan & Di Domenico, 2022, p. 451). In online settings, it functions much like a message from the firm to the customer, conveying credibility and intent. As a result, transparency and fairness in pricing are critical for sustaining loyalty and long-term relationships with consumers (Valldosera Grifoll, 2025, p. 31).

Yet AI-driven dynamic pricing systems can disrupt this balance when they assign different prices to customers who appear similar. If fairness considerations are absent, algorithmic models may systematically disadvantage certain groups, reinforcing inequality (Araf et al., 2024, p. 29). For this reason, pricing algorithms must be designed to optimize performance while also reflecting principles of justice. When consumers understand how their prices are set, trust tends to increase, whereas when the process is opaque, perceptions of exploitation quickly emerge.

Although digital nudging techniques can stimulate immediate sales, their long-term impact on trust is far more fragile. As Weinmann, Schneider, and vom Brocke (2016) demonstrate, how a choice is presented shapes consumer decisions as much as the underlying price itself, extending to how consumers experience the purchasing process. Preserving ethical limits in AI-based pricing is therefore essential for protecting both brand reputation and consumer confidence. Price is no longer merely a reflection of

market forces. It is shaped by emotional and moral evaluations. Consequently, modern marketing must aim not just to set the “right” price, but to build a perception of pricing that is both fair and trustworthy (Valldosera Grifoll, 2025, p. 27).

5.3. The Interaction Between Artificial Intelligence and Neuromarketing

The incorporation of artificial intelligence into marketing has made it possible to examine consumer behavior through visible purchase actions and through subtler behavioral and psychological signals as well. Pricing algorithms increasingly draw on cues such as browsing duration, click patterns, and past purchase history to infer how a given consumer is likely to respond to a price. Kahneman (2011) shows that many of these responses are governed by fast, intuitive judgment rather than deliberate calculation, which gives firms a clear incentive to design pricing strategies that speak to this intuitive layer of decision-making rather than to reasoned cost comparison alone.

By grounding pricing decisions in behavioral rather than purely rational models, firms move beyond static price-setting toward strategies that respond to psychological cues. Weinmann, Schneider, and vom Brocke (2016) describe how digital nudging techniques use small design choices, such as scarcity messages, urgency framing, and default options, to steer consumer decisions in fairly predictable directions. In this context, price no longer functions only as an economic indicator. It also becomes part of a broader communicative strategy aimed at shaping how a purchase feels to the person making it. Nunan and Di Domenico (2022) argue that this shift blurs the line between informing consumers and influencing them, since the same behavioral data used to personalize offers can also be used to exploit psychological vulnerabilities.

Despite these advances, the growing use of behavioral and psychological data in pricing introduces serious ethical and privacy challenges. Li (2022) argues that current data protection frameworks, including the GDPR, do not adequately address pricing systems built on inferred psychological profiles rather than on information consumers have explicitly shared. As AI systems move from merely describing consumer behavior to actively shaping it, the traditional boundaries around marketing ethics and consumer consent must be reconsidered.

As AI systems continue to improve their ability to anticipate psychological and emotional responses, pricing strategies are shifting from passive observation of consumer behavior toward active efforts to influence it. In this evolving setting, prices and brand messaging are evaluated not only on factual grounds but also through the emotional experience they create. Marketing thus enters a stage in which understanding the deeper psychological layers of consumer decision-making becomes as important as understanding cost structures or market demand.

6. Interaction Between Economic Rationality and Psychological Dynamics

6.1. Rationality and the Behavioral Dimension of Price in the Age of Artificial Intelligence

Classical economic theory is built on the assumption that individuals behave as rational agents who possess full information and seek to maximize their own utility. In reality, however, decisions are made in contexts marked by uncertainty, unequal information, and emotional influence. Kahneman’s (2011) dual-process account of judgment shows that price operates as an economic signal and, at the same time, as a cognitive trigger. Within AI-driven markets, algorithms analyze past choices to identify which price levels consumers interpret as “fair” or “acceptable,” thereby turning price from a simple market indicator into a behavioral stimulus.

Once AI is integrated into decision systems, the meaning of rationality itself begins to change. Prices are no longer set exclusively through human preferences but increasingly through the adaptive learning processes of algorithms. Although this shift improves efficiency, it also creates the risk that personalized pricing may weaken trust and undermine social welfare (Valldosera Grifoll, 2025). The price that maximizes efficiency is not necessarily the one that best serves equity, which highlights the importance of placing ethical limits on algorithmic rationality. Spann et al. (2024) add that these dynamics require

regulators to assume new responsibilities and strengthen transparency mechanisms in order to protect fairness in pricing, since price in the AI era must be understood as a multidimensional construct situated at the intersection of economic logic, cognitive processes, and ethical considerations.

6.2. Information Asymmetry and Algorithmic Monopoly

Information asymmetry has long been recognized as a central problem in economic theory. Although classical models assume that market participants have comparable access to information, this assumption no longer holds in digital environments. AI systems now control massive volumes of consumer data, giving them a decisive informational advantage and transforming price formation into a product of data-driven learning rather than open market exchange.

By relying on simple learning rules that update only from their own past outcomes rather than from a complete model of rival behavior, AI-based pricing systems can settle on prices well above competitive levels even without directly observing competitors' prices (Asker, Fershtman, & Pakes, 2021). Asker et al. (2021) are careful to note that such outcomes need not amount to collusion in any legal sense, since they can arise as a weakly dominant strategy without any agreement between firms. Even so, the mutual learning processes of algorithms can cause prices to converge, weakening genuine rivalry and pushing markets toward algorithmic monopolization.

Because these systems are typically designed to maximize short-term profits, they often evolve toward similar pricing patterns, gradually eroding competitive balance. Brown and MacKay (2021) show that firms with faster pricing technology can credibly commit to reacting to rivals' prices, allowing algorithms to reach shared, elevated pricing outcomes without any explicit human coordination. In such settings, prices are driven less by consumer preferences than by interactions among algorithms themselves.

The opaque nature of these mechanisms presents a major challenge for regulators. AI-driven systems operate at speeds that far exceed the ability of supervisory institutions to respond, making traditional antitrust tools increasingly ineffective (Spann et al., 2024). Conventional definitions of cartels, which depend on intentional agreement, fail to capture the subtle alignment that emerges from algorithmic learning processes.

Algorithmic monopolization also introduces ethical and privacy-related risks. Zhao, Jiang, and Yu (2025, p. 9) propose the use of local differential privacy to limit information sharing across algorithms and protect competitive conditions. Yet such safeguards can weaken learning performance, highlighting a difficult trade-off between efficiency and fairness.

Algorithmic decision systems are becoming increasingly autonomous, capable of driving markets toward convergence without human intervention. While this autonomy can improve efficiency, it also reduces competitive pressure and can harm consumer welfare. Araf et al. (2024, p. 29) further warn that algorithms can develop their own forms of bias when human oversight of non-linear decision logic is absent, pointing to evidence that pricing algorithms learned from ridehailing patterns have reflected neighborhood demographics and produced discriminatory outcomes for certain groups of consumers.

In the digital economy, then, information asymmetry extends beyond economics into the realms of ethics, regulation, and social justice. As algorithms reshape competitive dynamics through their learning capacity, they also blur the boundary between efficiency and fairness. Brown and MacKay (2021) show that this dynamic can persist even after mergers, with algorithmic competition generating larger post-merger price increases than standard Bertrand competition would predict, making traditional antitrust benchmarks harder to apply.

7. The Future Pricing Paradigm: Ethics, Transparency, and Sustainability

Although AI-based pricing systems promise substantial gains in efficiency, they increasingly raise concerns about ethical boundaries. Kaplan and Haenlein (2020) stress that technological optimization

does not automatically produce fair outcomes and that the gradual removal of human oversight weakens ethical control. While short-term efficiency can improve firm performance, it often creates long-term risks for transparency and consumer trust. When algorithms are evaluated only through performance metrics, ethical consistency can be undermined and the interests of vulnerable consumer groups may be overlooked.

Brown and MacKay (2021) show that algorithmic pricing can meaningfully reduce consumer surplus even without any collusive intent, simply as a byproduct of firms' incentives to invest in faster pricing technology. For this reason, ethical responsibility cannot rest solely with software engineers but must also involve corporate leadership and governance structures. Without institutional ethical guidelines, AI tools can easily be deployed in manipulative ways. Zhao, Jiang, and Yu (2025) identify the trade-off between privacy and efficiency as one of the most fragile points in algorithmic pricing: local differential privacy protects user data, yet it also limits the system's capacity to learn. Sustainable AI-based pricing depends, in turn, on balancing ethical safeguards with economic performance.

Digital nudging presents another source of ethical tension. Weinmann, Schneider, and vom Brocke (2016) argue that nudging techniques can subtly convert deliberate consumer choices into guided responses. While this may boost efficiency in the short term, it risks undermining trust over time. This tension points toward what can be described as an ethical rationality, in which efficiency gains only acquire true value when they are accompanied by justice, trust, and moral responsibility.

Adams et al. (2025) show that the diffusion of AI-based pricing is closely tied to firm performance, with adopting firms displaying stronger sales growth and markups as well as greater sensitivity to monetary policy shocks. Valldosera Grifoll (2025) raises a related concern, noting that the opacity of many AI-driven pricing models, which function as "black boxes" whose internal reasoning remains invisible to outside observers, can damage consumer confidence in pricing fairness. As a result, future pricing regimes will increasingly depend on algorithmic governance built around transparency and explainability.

Concerns about discrimination and data protection further reinforce this shift. Li (2022) highlights the thin line between legitimate data use and discriminatory pricing, drawing on the concept of "group privacy" as a foundation for future regulation. Under this perspective, the success of AI systems will be judged not only by their accuracy or profitability but also by their ethical compliance. This can be described as a form of ethical intelligence becoming an essential component of market intelligence, an extension that is consistent with Kaplan and Haenlein's (2020) broader argument that consumer trust and firm-level ethical guidelines will be decisive for how AI-based pricing systems are accepted by society.

From a sustainability perspective, Araf et al. (2024) argue that pricing strategies of the future must reconcile efficiency with social welfare. They define "sustainable AI pricing" as an approach that evaluates pricing systems across economic, social, and environmental dimensions rather than prioritizing profit alone. Spann et al. (2024) add that preventing tacit collusion in algorithmic markets requires regulatory systems that are as dynamic and data-driven as the algorithms they oversee.

In the AI era, economic efficiency only acquires real significance when evaluated alongside fairness, trust, and ethical responsibility. Pricing systems of the future will therefore evolve toward frameworks that combine behavioral adaptability, moral sensitivity, and technological transparency. As Yilmazel (2024) notes, AI brings together mechanical, analytical, and emotional capacities within marketing practice, a combination that extends naturally to how firms approach pricing decisions.

8. Conclusion

AI-driven pricing systems mark a major evolutionary shift in how markets operate and how economic behavior is understood. Whereas traditional pricing theories rest on assumptions of rational actors and stable equilibria, decision-making in the digital economy is now shaped by algorithmic learning, large-

scale data analytics, and behavioral insight. For this reason, economic efficiency can no longer be assessed solely through productivity but must also be evaluated in relation to cognitive coherence, ethical responsibility, and social trust.

In today's digital marketplaces, price is not simply a numerical indicator. It has become a convergence point where consumer psychology, data flows, and digital ethics meet. Although the predictive capacity of algorithms can improve market performance, it also introduces serious risks, including manipulation, lack of transparency, and data-based inequality. For this reason, the future of the digital economy depends on governance structures capable of balancing technological advancement with human values.

The long-term viability of AI-based pricing depends as much on ethical accountability as on technical precision. Market stability is closely linked to the degree of trust that participants place in pricing systems. Accordingly, explainability, data integrity, and the ability to audit algorithmic decisions have become essential pillars of economic sustainability. If ethical oversight is absent, short-term efficiency gains will be undermined by long-term losses in social welfare, ultimately limiting the benefits that AI can deliver.

From a policy perspective, the central challenge is to design regulatory frameworks that embed ethics and transparency into digital pricing. This includes empowering independent bodies to oversee algorithmic systems, modernizing data-protection laws, and implementing digital ethics standards consistent with international norms. In addition, improving consumer understanding of algorithmic pricing through price-literacy initiatives can help reduce information asymmetries and strengthen trust and fairness in digital markets.

For firms, future success will hinge on technological investment and, just as much, on the ability to deploy AI within a human-centered strategy. The ethical management of algorithmic pricing is rapidly becoming a key driver of brand credibility and customer loyalty. Companies must, in turn, establish internal governance structures that integrate transparency, data protection, and social responsibility directly into their pricing systems.

This study is also subject to certain limitations that point toward directions for future research. As a conceptual and narrative literature review, it does not provide direct empirical testing of the relationships it proposes between algorithmic rationality, consumer trust, and price fairness. Future research could address this limitation in several ways. Experimental or survey-based studies could test how specific algorithmic pricing designs affect perceived fairness and trust across different consumer segments, while comparative studies across industries and regulatory environments would help clarify whether the ethical risks identified here vary systematically by sector. In addition, future work could examine how emerging regulatory instruments, such as algorithmic auditing requirements and data-protection reforms, actually change firm behavior in practice, rather than assessing them only at the level of policy design. Longitudinal research tracking the evolution of algorithmic pricing systems over time would further help determine whether the learning equilibria described in this study stabilize, intensify, or give way to new forms of market coordination. From a policy standpoint, the recommendations discussed above should be treated not as isolated measures but as complementary components of a single governance architecture, in which regulatory oversight, corporate accountability, and consumer literacy reinforce one another rather than operating in isolation.

Ultimately, pricing in the age of artificial intelligence has moved far beyond a tool of economic optimization. It now operates as a multidimensional decision architecture that incorporates ethical, social, and political considerations. The sustainability of the digital economy will depend on whether efficiency can be aligned with fairness, innovation with ethical awareness, and competition with social welfare. In this sense, pricing under AI has become a matter of social governance. When guided by a human-centered vision, AI has the potential to create markets that are more efficient, and also more just, resilient, and worthy of trust.

End Notes

There are no end notes in this study.

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Araştırma Makalesi

Rasyonel Fiyattan Algoritmik Rasyonaliteye: Yapay Zekâ Destekli Fiyatlandırmada Davranışsal Dönüşüm

From Rational Price to Algorithmic Rationality: Behavioral Transformation in Artificial Intelligence–Driven Pricing

Ahmet KASAP Assoc. Prof. Dr., Tokat Gaziosmanpaşa University Turhal Faculty of Applied Sciences ahmet.kasap@gop.edu.tr https://orcid.org/0000-0001-7231-2693	Mustafa KARAKUŞ Assoc. Prof. Dr., Ankara Hacı Bayram Veli University Faculty of Financial Sciences mustafa-karakus@hbv.edu.tr https://orcid.org/0000-0001-7207-6686
Feyzullah TECİRLİ Dr., Mersin University Anamur Vocational School feyzullah.tecirli@mersin.edu.tr https://orcid.org/0000-0002-3565-7905	Çınar KAYA Dr., Tokat Gaziosmanpaşa University Turhal Faculty of Applied Sciences cinar.kaya@gop.edu.tr https://orcid.org/0009-0007-7268-2943

Genişletilmiş Özet

Bu çalışma, yapay zekâ destekli fiyatlama mekanizmalarının günümüz ekonomilerinde fiyatın anlamını nasıl yeniden tanımladığını ele almakta ve klasik iktisadın rasyonel fiyat kavrayışından, davranışsal ve algoritma temelli bir düzene doğru gerçekleşen dönüşümü çözümlemektedir. Dijitalleşmenin hız kazanması, büyük verinin yaygınlaşması ve otomasyonun derinleşmesiyle birlikte fiyat, artık yalnızca maliyet ve arz–talep dengesinin bir çıktısı olmaktan uzaklaşmış ve tüketici psikolojisi, veri işleme kapasitesi ve makine öğrenmesi süreçlerinin kesiştiği çok katmanlı bir yapıya bürünmüştür. Oysa geleneksel iktisat, fiyatı rasyonel bireylerin fayda ve kâr maksimizasyonu hedefleri doğrultusunda aldığı kararların sonucu olarak tanımlar. Bu çerçevede tüketici bütçesi içinde en yüksek faydayı ararken, firmalar maliyetlerini ve rekabet koşullarını dikkate alarak fiyatlarını belirler. Ancak davranışsal ekonomi literatürü, bireylerin gerçekte bu denli tutarlı ve hesapçı olmadığını, fiyatı çoğu zaman duygusal, sezgisel ve bağlama duyarlı biçimde değerlendirdiklerini göstermiştir.

Bir fiyat, insanlar açısından yalnızca sayısal bir değer olmayıp adalet, kalite, güven ve değer algılarının da taşıyıcısıdır. Yapay zekâ teknolojileri ise bu davranışsal boyutu algoritmik düzleme taşımış, fiyatlamayı daha ince ayarlı ve kişiye özgü hâle getirmiştir. Günümüzde algoritmalar, tüketicilerin dijital izlerini takip ederek hangi ürünlere yöneldiklerini, hangi fiyat aralıklarında satın alma eğilimi gösterdiklerini, hangi zamanlarda daha istekli olduklarını ve hangi kampanyalara tepki verdiklerini çözümleyebilmektedir. Bu veriler aracılığıyla her birey için özgül fiyat profilleri oluşturulmakta ve fiyatlar anlık olarak güncellenmektedir. Böylece fiyat, ürün maliyetinden çok, tüketicinin ödeme istekliliğine göre şekillenen bir değişkene dönüşmektedir. Bu süreç, fiyatı sabit bir etiket olmaktan çıkarıp dinamik ve kişiselleştirilmiş bir karar aracına dönüştürmektedir.

Çalışmada merkezi bir yer tutan “algoritmik rasyonalite” kavramı, bu yeni fiyatlama düzenini açıklamak için kullanılmaktadır. Klasik iktisatta rasyonel karar verme insan zihnine atfedilirken, dijital ekonomide bu işlev giderek makinelere aktarılmaktadır. Algoritmalar piyasayı sürekli izler, fiyat değişimlerine verilen tepkileri kaydeder ve elde edilen geri bildirimler üzerinden yeni fiyat stratejileri üretir. Bu bağlamda piyasa dengesi sabit bir nokta olmaktan çıkar, zira her yeni veri, sistemi yeniden ayarlayan bir sinyal hâline gelir. Fiyatlar da bu kesintisiz öğrenme sürecinin çıktısı olarak sürekli değişir. Algoritmaların bu biçimde öğrenerek fiyat belirlemesi, piyasa yapısının doğasını kökten dönüştürmektedir.

Farklı firmaların kullandığı fiyatlama yazılımları, rakip fiyatlarını ve tüketici tepkilerini izleyerek zamanla benzer davranış kalıpları geliştirebilir. Bu da firmalar arasında açık bir anlaşma olmaksızın fiyatların birbirine yaklaşmasına ve rekabetin zayıflamasına yol açabilir. Böyle bir ortamda fiyatlar artık bilinçli insan kararlarından çok, makineler arası etkileşimin ürünü hâline gelir. Bu durum geleneksel rekabet anlayışını zorlamakta ve piyasada örtük bir koordinasyon riskini doğurmaktadır. Kısa vadede kârı artırmaya odaklanan algoritmalar, uzun vadede fiyat düzeylerini yükselterek tüketici refahını azaltabilir. Dolayısıyla yapay zekâ temelli fiyatlama, yalnızca teknik değil, aynı zamanda düzenleyici ve etik bir sorun alanı hâline gelmektedir.

Literatürde kişiselleştirilmiş fiyatlamamanın tüketici güveni üzerindeki etkisi özellikle vurgulanmaktadır. Aynı ürünü alan iki kişinin farklı fiyatlarla karşılaşması, adaletsizlik algısını tetikleyebilmektedir. Fiyatın hangi mantıkla belirlendiğinin bilinmemesi ise algoritmaların tüketiciyi manipüle ettiği düşüncesini güçlendirmektedir. Bu durum dijital piyasalara duyulan güveni aşındırmakta ve marka sadakatini zayıflatmaktadır. Bu bağlamda fiyat, yalnızca bir ödeme tutarı olmayıp firma ile tüketici arasındaki ilişkinin de bir göstergesi hâline gelmektedir. Şeffaf olmayan fiyatlama yapıları, bireyde sömürüldüğü ya da aldatıldığını hissinin doğurabilmektedir. Bu nedenle makale, yapay zekâ destekli fiyatlama sistemlerinin yalnızca verimlilik açısından değil, etik ve toplumsal boyutlarıyla da değerlendirilmesi gerektiğini savunmaktadır.

Bunun yanı sıra çalışma, dijital dürtme ve nöropazarlama uygulamalarının yapay zekâ ile birleşerek fiyatın psikolojik etkisini daha da güçlendirdiğini ortaya koymaktadır. Algoritmalar, sayfada kalma süresi, tıklama davranışları ve görsel tepkiler gibi mikro sinyallerden bireyin duygusal durumunu tahmin edebilmektedir. Kıtlik vurguları, zaman baskısı ve sosyal kanıt mesajları, fiyat duyarlılığını azaltmak ve satın alma kararını hızlandırmak amacıyla devreye sokulmaktadır. Böylece fiyat, rasyonel bir değerlendirme unsurundan çok, duygusal bir tetikleyiciye dönüşmektedir. Kısa vadede satışları artırabilen bu mekanizma, uzun vadede güven kaybına ve piyasa istikrarsızlığına zemin hazırlayabilmektedir. Aynı zamanda bu süreçler veri gizliliği ve mahremiyet açısından da ciddi riskler doğurmaktadır.

Çoğu tüketici, dijital ortamlarda bıraktığı izlerin fiyatlama süreçlerinde nasıl kullanıldığının farkında değildir. Arama geçmişleri, alışveriş alışkanlıkları ve çevrim içi davranış kalıpları, algoritmalar tarafından analiz edilerek bireylerin ödeme istekliliği tahmin edilmektedir. Bu durum, kişisel verileri ekonomik bir kaynağa dönüştürmektedir. Algoritmalar, bu veriler üzerinden bireylerin kırılgan noktalarını saptayarak onları daha yüksek fiyatlarla karşı karşıya bırakabilmektedir. Özellikle düşük gelirli veya dezavantajlı gruplar, bu sistemlerde sistematik biçimde daha olumsuz koşullarla karşılaşma riski taşımaktadır. Böylece yapay zekâ, toplumsal eşitsizlikleri yeniden üreten bir mekanizma hâline gelebilir.

Bu nedenle makale, geleceğin fiyatlama sistemlerinin etik yönetim ilkeleriyle uyumlu biçimde tasarlanması gerektiğini vurgular. Yapay zekâ, yalnızca kâr artırmak için değil, adil ve sürdürülebilir piyasa yapıları kurmak amacıyla da kullanılmalıdır. Fiyat algoritmaları, tüketici haklarını, veri gizliliğini ve toplumsal refahı gözetken sınırlar içinde çalışmalıdır. Aksi takdirde kısa vadeli verimlilik kazanımları, uzun vadede güven kaybı ve piyasa istikrarsızlığına yol açacaktır. Şeffaflık ve açıklanabilirlik bu bağlamda dijital fiyatlama sistemlerinin temel yapı taşları hâline gelmektedir.

Tüketicilerin kendilerine sunulan fiyatların hangi mantıkla belirlendiğini anlayabilmesi, güvenin korunması açısından kritik önemdedir. Aynı şekilde algoritmaların bağımsız biçimde denetlenebilmesi ve hatalı ya da ayrımcı sonuçların tespit edilebilmesi gerekir. Makale bu noktada “etik rasyonalite” kavramını öne çıkarmaktadır. Bu yaklaşımda ekonomik etkinlik, toplumsal adalet ve bireysel haklarla birlikte ele alınır. Fiyat, artık yalnızca kârı maksimize eden bir araç olmayıp piyasa düzeninin ve sosyal güvenin de bir göstergesi olarak değerlendirilir.

Yapay zekâ destekli fiyatlama sistemleri uygun yönetimle piyasa etkinliğini artırabilir, ancak etik bir çerçeve olmaksızın uygulandıklarında sosyal refahı ve piyasa adaletini zedeleyebilirler. Bu nedenle teknoloji ile etik arasında kurulan denge, geleceğin fiyatlama paradigmasını belirleyecek temel unsurlardan biri olacaktır. Çalışma, yapay zekâ çağında fiyatın artık yalnızca ekonomik bir değişken olmayıp davranışsal, psikolojik ve etik boyutları olan bir yapı hâline geldiğini bütüncül biçimde ortaya koymaktadır.

Dijital piyasalarda fiyat, tüketici algılarını biçimlendiren, güven düzeylerini etkileyen ve rekabetin yönünü belirleyen merkezi bir mekanizmaya dönüşmüştür. Algoritmalar tarafından belirlenen fiyatlar, bireylerin kararlarını yönlendirmekle kalmamakta, aynı zamanda neyin adil, neyin kabul edilebilir ve neyin makul olduğuna dair algılarını da şekillendirmektedir. Bu nedenle fiyatlama, artık yalnızca işletmelerin gelir stratejisinin bir parçası değil, aynı zamanda toplumsal düzenin de bir bileşenidir. Araştırma, geleceğin ekonomik sistemlerinde fiyatın bu çok katmanlı rolünün daha da belirleyici olacağını ileri sürmektedir.

Yapay zekâ temelli fiyatlama doğru kullanıldığında piyasa etkinliğini artırabilir, kaynak tahsisini iyileştirebilir ve tüketiciye daha uygun teklifler sunabilir. Ancak bu sistemler yalnızca teknik performans ölçütleriyle yönetildiğinde, adalet, güven ve şeffaflık gibi temel değerleri aşındırma riski taşır. Bu nedenle dijital ekonomide gerçek başarı, yalnızca daha akıllı algoritmalar geliştirmekle değil, bu algoritmaları insan merkezli bir çerçevede yönlendirmekle mümkün olacaktır.

Makale, politika yapıcılar ve düzenleyici kurumlar için de önemli çıkarımlar sunmaktadır. Geleneksel rekabet ve fiyat denetimi politikalarının, algoritmaların hızına ve karmaşıklığına uyum sağlayacak biçimde güncellenmesi gerekmektedir. Algoritmik fiyatlama sistemlerinin denetlenebilir olması, piyasa adaletinin korunması açısından hayati önemdedir. Aynı şekilde firmalar için de etik yönetim artık bir tercih değil, zorunluluktur. Şirketlerin fiyatlama algoritmalarını tasarlarken yalnızca kârı değil, uzun vadeli güveni ve toplumsal sorumluluğu da gözetmeleri gerekmektedir.

Bu çalışma, yapay zekâ çağında fiyatın doğasının köklü biçimde değiştiğini ve bu dönüşümün hem ekonomik teoriyi hem de piyasa uygulamalarını yeniden şekillendirdiğini ortaya koymaktadır. Fiyat artık arz ve talebin kesişim noktası olmaktan çıkmış ve veri, algoritma, psikoloji ve etik değerlerin birleştiği bir karar alanına dönüşmüştür. Dijital ekonominin sürdürülebilirliği, bu alanın nasıl yönetileceğine bağlıdır. Gerçek ilerleme ise verimlilik ile adaletin, teknoloji ile insanî değerlerin ve otomasyon ile sorumluluğun birlikte var olabildiği bir fiyatlama düzeninin kurulmasıyla mümkün olacaktır.