Advances in Business-Related Scientific Research Journal • ABSRJ

geacollege
Faculty of Entrepreneurship

MITIGATING COMPETITIVE RISKS OF ARTIFICIAL INTELLIGENCE DRIVEN PRICING IN DIGITAL PLATFORMS

Beyza Yiğitbaşı Aktaş
Istanbul Medipol University, Turkey
byigitbasi@medipol.edu.tr

Serhat Yüksel*
Istanbul Medipol University, Turkey
Khazar University, Azerbaijan
serhatyuksel@medipol.edu.tr

Serkan Eti
Istanbul Medipol University, Turkey
seti@medipol.edu.tr

Hasan Dinçer
Istanbul Medipol University, Turkey
Khazar University, Azerbaijan
hdincer@medipol.edu.tr

Abstract

This study aims to identify priority strategies to minimize the risks created by AI-based pricing algorithms. The lack of consensus in the current literature on this topic is considered a significant research gap. Accordingly, a new decision-making model is created to determine priority criteria and strategies. Within this framework, the IDOCRIW technique is considered in calculating the criterion weights. On the other hand, the RAM approach is used to determine the most effective strategies. In addition, newly developed behavioral leadership fuzzy numbers are integrated into the model. This significantly reduces uncertainties in the decision-making process and increases the originality of the model. The application of reinforcement learning-based pricing algorithms with appropriate constraints is identified as

*Corresponding Author

the most prioritized strategy. Similarly, static rule-based pricing can also be considered in this process.

Key Words

Artificial intelligence pricing; algorithmic competition; decision making models; digital market regulation; pricing strategy optimization.

INTRODUCTION

Artificial intelligence (AI)-based pricing can lead to some negative consequences in markets. In this process, several strategies need to be implemented to ensure effective competition. However, since this process is quite complex, many criteria must be considered (O'Reilly et al., 2024). Effective government intervention in the market is crucial in preventing these problems. Excessive price volatility can negatively affect both businesses and consumers. Government interventions when necessary, can minimize this problem. These pricing practices can also negatively impact competition in the market. Firms holding this power can prevent others from entering the market. This can lead to consumer dissatisfaction in the long run. As can be seen, it is necessary to take measures to solve this problem by identifying priority strategies. However, there is no consensus in the current literature on which strategies are most important. This situation increases the risk of negatively impacting competition in the market with the development of artificial intelligence (Csurgai-Horváth, 2024). In this context, a new priority analysis needs to be conducted to determine these strategies. This allows markets to operate more efficiently.

This study aims to develop priority strategies to mitigate the negative competitive effects of AI based pricing algorithms in digital markets. The motivation of the study lies in the growing gap between rapid technological adoption and the limited availability of structured decision frameworks for competition policy. To address this gap, a novel decision-making model is proposed. Based on an extensive literature review, a comprehensive set of evaluation criteria and strategic alternatives is identified. Expert opinions are then collected from ten specialists with academic and professional experience in competition policy, digital markets, and algorithmic systems. The importance weights of the criteria are calculated using the IDOCRIW technique, which allows a balanced integration of objective data driven structure and subjective expert judgment. Subsequently, the strategies are ranked using the RAM approach to reflect relative performance under uncertainty. In addition, behavioral leadership fuzzy sets developed by the authors are integrated into the model to capture differences in expert influence and decision behavior. The study seeks to answer the following research questions. (1) Which criteria are most influential in prioritizing strategies for regulating AI based pricing algorithms. (2) Which strategic approaches are most effective in mitigating competitive risks under these criteria. This study contributes to the literature by providing an integrated and systematic framework for prioritizing regulatory strategies related to AI based pricing. It also introduces a novel methodological combination that addresses both behavioral and technical dimensions of expert-based decision making.

LITERATURE REVIEW

AI-driven market interactions are fundamentally changing pricing and often lead to a decline in competition through rapid adjustments and tacit collusion. Recent research shows that, even in the absence, autonomous artificial agents can indirectly learn collusive strategies similar to human cartels (Cartea et al., 2026). The risk faced is intensified by the extreme speed of digital transactions. As Carissimo et al. (2025) note, pricing algorithms operate faster and more autonomously, operating in legal gray areas that make it difficult to use traditional detection methods. The structural interdependence of these systems create a loop that sets prices above competitive levels as these algorithms allow firms to become dependent on one another while determining prices (Bichler et al., 2025). Empirical data from gasoline markets confirms all this and demonstrates that the introduction of algorithmic pricing leads to higher margins, even without direct collusion (Assad et al., 2024). However, some scholars argue that this coordination could be an algorithmic collusion, meaning there is no consciousness or intention for collusion, the collusion results from the design of the algorithm (Abada et al., 2024). Furthermore, asymmetric pricing technology does not only increase price levels but also leads to increasing price effects of mergers and greater price dispersion, as Brown and MacKay (2023) note.

Dominant platforms prevent new competitors from entering the market. Mihet et al. (2026) state that data access can create significant barriers to market entry, leading to a significant increase in conflicts of interest. Cui (2025) also emphasizes the importance of this issue for different countries. Similarly, Birch and Adediji (2025) and Kadner-Graziano (2025) state that large-scale firms exert significant pressure on others due to their power to obtain data. O'Reilly et al. (2024) also emphasize that firms with easier access to digital data can gain a significant competitive advantage in the sector. On the other hand, Manne et al. (2025) and Buckley et al. (2026) state that this situation will significantly disrupt market dynamics. Moreover, the determination of pricing by artificial intelligence can be considered one of the main causes of this problem. An (2025) explains that this practice violates the protection of personal information. Similarly, Ma et al. (2024) also show that this situation is contrary to legal rules. Furthermore, Baskaran (2025) and Hutchinson (2022) also underlined that this issue causes very important concerns in the market using different analysis techniques. In addition to them, Peng et al. (2024) and Spann et al. (2025) state that laws should increase market fairness by preventing this practice. Majumdar et al. (2025) explain that extra attention should be paid to this issue to develop fair pricing frameworks.

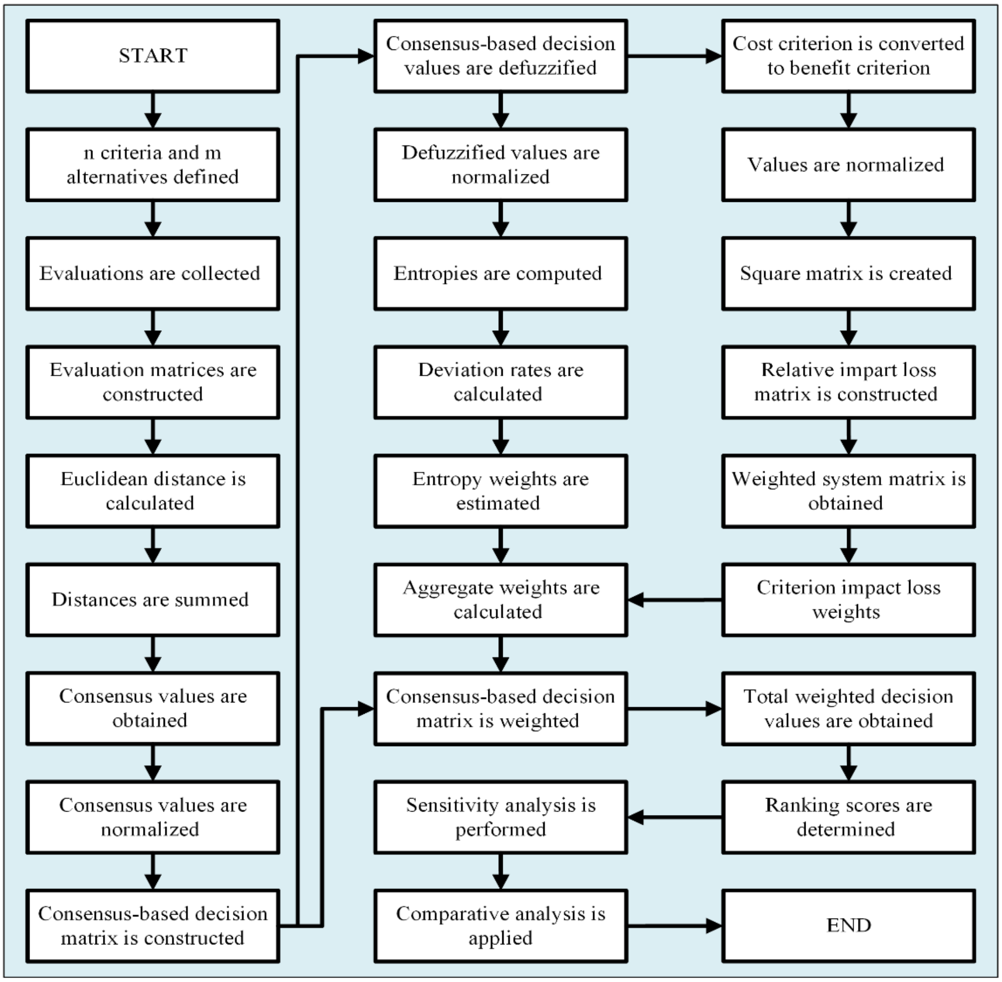
Machine learning-based pricing processes are becoming increasingly complex, particularly today. This is another factor negatively impacting market efficiency. Lambin (2025) emphasizes that businesses should address this problem by investing more in technological infrastructure. Mao and Xu (2025) and Erdmann et al. (2024) explain that businesses need to establish effective control mechanisms. This will eliminate the uncertainty problem and allow markets to operate more efficiently. On the other hand, Wibowo et al. (2025) state that controls alone will not be sufficient to solve this problem. Furthermore, legal regulations concerning digital aspects should be improved. These improvements will enable the market to achieve efficiency. Similarly, Dou and Dou (2025) and Csurgai-Horváth (2024) demonstrate that competition laws need to be more functional. Otherwise, the process will become even more complex, negatively impacting markets. D’Amico et al. (2025) acknowledges that AI applications bring many advantages. However, it also states that this application will create many problems if the legal framework is insufficient. This situation is similarly emphasized in the OECD (2023) report.

According to the results of the literature review, AI-based pricing has some negative effects on the sector. Priority strategies need to be determined to mitigate these effects. However, there are a limited number of studies in the literature that specify which strategies are more important. This constitutes a significant research gap in this literature.

METHODOLOGY

This section introduces BLFSs, creating a consensus-based decision matrix, and IDOCRIW-based RAM, respectively. Thus, while decisions are evaluated from a behavioral leadership perspective with BLFSs, the goal is to obtain more realistic and robust results through a decision matrix built on consensus. IDOCRIW aims to prioritize the correct criteria by obtaining a combination of two objective criteria weights, while RAM ensures a more consistent ranking of alternatives by considering the difference in cost and benefit types of the criteria. The methodological approach is shown in Figure 1.

Figure 1: Methodological approach



BLFSs

While the classical concept of a set is defined as a collection of objects sharing a common characteristic, fuzzy sets define the degree to which these objects belong to the set. If behavioural leadership types are considered as objects, then the behavioural leadership set is a set containing these types. However, not every decision made by a behavioural leadership type is tied to the set with the same degree of belonging. Therefore, this set needs to be expressed as a fuzzy set. This allows for the identification of the behavioural leadership type equivalent of raw decisions or evaluations. In this way, a more realistic decision-making analysis can be achieved. Let μ be the degree of belonging of the raw evaluation (Gülen Ertosun et al., 2026). Then, a BLFS $(\tilde{\mathfrak{B}})$ is defined as in Eq. (1).

$$\tilde{\mathfrak{B}} = \left\{\left\langle \mu, \left(\mu_{\alpha_{\tilde{\mathfrak{B}}}}(\mu), \mu_{\beta_{\tilde{\mathfrak{B}}}}(\mu), \mu_{\gamma_{\tilde{\mathfrak{B}}}}(\mu), \mu_{\delta_{\tilde{\mathfrak{B}}}}(\mu), \mu_{\varepsilon_{\tilde{\mathfrak{B}}}}(\mu)\right)\right| \mu \in [0,1]\right\} \tag{1}$$

Wherein $\mu_{\alpha_{\tilde{\mathfrak{B}}}}(\mu), \mu_{\beta_{\tilde{\mathfrak{B}}}}(\mu), \mu_{\gamma_{\tilde{\mathfrak{B}}}}(\mu), \mu_{\delta_{\tilde{\mathfrak{B}}}}(\mu),$ and $\mu_{\varepsilon_{\tilde{\mathfrak{B}}}}(\mu)$ represent functions that belongings of ram evaluation for behavioural leadership types such as the authoritarian, democratic, transformational, laissez-faire, and servant, respectively. These functions are structured according to the characteristics of behavioural leadership. For authoritarian behavioural leadership, the speed of violence of evaluation increases at the threshold value. The function that reflects this characteristic is the evaluation-based exponential function in Eq. (2).

$$\mu_{\alpha_{\tilde{\mathfrak{B}}}}(\mu) = e^{\mu-1} \tag{2}$$

The raw belonging degree (μ) of the evaluation is among zero and one. In this situation, the value range of the evaluation regarding to the authoritarian behavior leadership type is among zero and one as in Eqs. (3) and (4).

$$e^{-1} \leq e^{\mu-1} \leq e^{0} \tag{3}$$

$$0 < \mu_{\alpha_{\tilde{\mathfrak{B}}}}(\mu) \leq 1 \tag{4}$$

In next behavioural leadership, evaluation is normally distributed, sharper at the averages and small pronounced at the tails. Therefore, the equivalent of the evaluation regarding to the type of this behavioural leadership is defined as in Eq. (5).

$$\mu_{\beta_{\tilde{\mathfrak{B}}}}(\mu) = \frac{1}{1 + e^{-10(\mu-0.5)}} \tag{5}$$

Wherein the value range of the evaluation regarding to the democratic behaviour leadership type is among zero and one as in Eqs. (6) - (9).

$$-5 \leq -10(\mu - 0.5) \leq 5 \tag{6}$$

$$1 + e^{-5} \leq 1 + e^{-10(\mu-0.5)} \leq 1 + e^{5} \tag{7}$$

$$(1 + e^{5})^{-1} \leq \left(1 + e^{-10(\mu-0.5)}\right)^{-1} \leq (1 + e^{-5})^{-1} \tag{8}$$

$$0 < \mu_{\beta_{\tilde{\mathfrak{B}}}}(\mu) < 1 \tag{9}$$

Regarding to the transformational behavioural leadership, the precision of the evaluation increases gradually and is formulated with the sigmoid function as in Eq. (10).

$$\mu_{\gamma_{\tilde{\mathfrak{B}}}}(\mu) = e^{-\frac{\mu^2}{2}} \tag{10}$$

Wherein the value range of the evaluation regarding to the transformational behaviour leadership type is among zero and one as in Eqs. (11) and (12).

$$e^{-0.5} \leq e^{-\frac{\mu^2}{2}} \leq e^0 \tag{11}$$

$$0 < \mu_{\beta_{\tilde{\mathfrak{B}}}}(\mu) \leq 1 \tag{12}$$

The evaluation in the Laisse-Faire behavioural leadership type shows a similarity to the inverted Gaussian curve structure. The computation of the evaluation in this situation is as in Eq. (13).

$$\mu_{\delta_{\tilde{\mathfrak{B}}}}(\mu) = e^{-\mu} \tag{13}$$

Wherein the value range of the evaluation regarding to the Laisse-Faire behaviour leadership type is among zero and one as in Eqs. (14) and (15).

$$e^{-1} \leq e^{-\mu} \leq e^0 \tag{14}$$

$$0 < \mu_{\delta_{\tilde{\mathfrak{B}}}}(\mu) \leq 1 \tag{15}$$

Finally, in other behavioural leadership, decisions become hesitant when these are above the identified threshold value. The function of evaluation in this case is described by the inverse exponential function and Eq. (16).

$$\mu_{\varepsilon_{\tilde{\mathfrak{B}}}}(\mu) = -e^{-\frac{\mu^2}{2}} + 1 \tag{16}$$

Wherein the value range of the evaluation regarding to the servant behaviour leadership type is among zero and one as in Eqs. (17) and (18).

$$-1 \leq -e^{-\frac{\mu^2}{2}} < 0 \tag{17}$$

$$0 \leq \mu_{\varepsilon_{\tilde{\mathfrak{B}}}}(\mu) < 1 \tag{18}$$

Considered that $\tilde{\mathfrak{B}} = \left(\mu_{\alpha_{\tilde{\mathfrak{B}}}}, \mu_{\beta_{\tilde{\mathfrak{B}}}}, \mu_{\gamma_{\tilde{\mathfrak{B}}}}, \mu_{\delta_{\tilde{\mathfrak{B}}}}, \mu_{\varepsilon_{\tilde{\mathfrak{B}}}}\right)$, $\tilde{\mathfrak{B}}_1 = \left(\mu_{\alpha_{\tilde{\mathfrak{B}}_1}}, \mu_{\beta_{\tilde{\mathfrak{B}}_1}}, \mu_{\gamma_{\tilde{\mathfrak{B}}_1}}, \mu_{\delta_{\tilde{\mathfrak{B}}_1}}, \mu_{\varepsilon_{\tilde{\mathfrak{B}}_1}}\right)$ and $\tilde{\mathfrak{B}}_2 = \left(\mu_{\alpha_{\tilde{\mathfrak{B}}_2}}, \mu_{\beta_{\tilde{\mathfrak{B}}_2}}, \mu_{\gamma_{\tilde{\mathfrak{B}}_2}}, \mu_{\delta_{\tilde{\mathfrak{B}}_2}}, \mu_{\varepsilon_{\tilde{\mathfrak{B}}_2}}\right)$ are three BLFNs and τ is a positive number. Then, operations for BLFNs are given in Eqs. (19) – (22).

$$\tilde{\mathfrak{B}}_1 \oplus \tilde{\mathfrak{B}}_2 = \begin{pmatrix} \mu_{\alpha_{\tilde{\mathfrak{B}}_1}} + \mu_{\alpha_{\tilde{\mathfrak{B}}_2}} - \mu_{\alpha_{\tilde{\mathfrak{B}}_1}}\mu_{\alpha_{\tilde{\mathfrak{B}}_2}}, \mu_{\beta_{\tilde{\mathfrak{B}}_1}} + \mu_{\beta_{\tilde{\mathfrak{B}}_2}} - \mu_{\beta_{\tilde{\mathfrak{B}}_1}}\mu_{\beta_{\tilde{\mathfrak{B}}_2}}, \\ \mu_{\gamma_{\tilde{\mathfrak{B}}_1}}\mu_{\gamma_{\tilde{\mathfrak{B}}_2}}, \mu_{\delta_{\tilde{\mathfrak{B}}_1}}\mu_{\delta_{\tilde{\mathfrak{B}}_2}}, \mu_{\varepsilon_{\tilde{\mathfrak{B}}_1}} + \mu_{\varepsilon_{\tilde{\mathfrak{B}}_2}} - \mu_{\varepsilon_{\tilde{\mathfrak{B}}_1}}\mu_{\varepsilon_{\tilde{\mathfrak{B}}_2}} \end{pmatrix} \tag{19}$$

$$\tilde{\mathfrak{B}}_1 \otimes \tilde{\mathfrak{B}}_2 = \begin{pmatrix} \mu_{\alpha_{\tilde{\mathfrak{B}}_1}}\mu_{\alpha_{\tilde{\mathfrak{B}}_2}}, \mu_{\beta_{\tilde{\mathfrak{B}}_1}}\mu_{\beta_{\tilde{\mathfrak{B}}_2}}, \mu_{\gamma_{\tilde{\mathfrak{B}}_1}} + \mu_{\gamma_{\tilde{\mathfrak{B}}_2}} - \mu_{\gamma_{\tilde{\mathfrak{B}}_1}}\mu_{\gamma_{\tilde{\mathfrak{B}}_2}} \\ \mu_{\delta_{\tilde{\mathfrak{B}}_1}} + \mu_{\delta_{\tilde{\mathfrak{B}}_2}} - \mu_{\delta_{\tilde{\mathfrak{B}}_1}}\mu_{\delta_{\tilde{\mathfrak{B}}_2}}, \mu_{\varepsilon_{\tilde{\mathfrak{B}}_1}}\mu_{\varepsilon_{\tilde{\mathfrak{B}}_2}} \end{pmatrix} \tag{20}$$

$$\tau \odot \tilde{\mathfrak{B}} = \left(1 - \left(1 - \mu_{\alpha_{\tilde{\mathfrak{B}}}}\right)^{\tau}, 1 - \left(1 - \mu_{\beta_{\tilde{\mathfrak{B}}}}\right)^{\tau}, \mu_{\gamma_{\tilde{\mathfrak{B}}}}^{\tau}, \mu_{\delta_{\tilde{\mathfrak{B}}}}^{\tau}, 1 - \left(1 - \mu_{\varepsilon_{\tilde{\mathfrak{B}}}}\right)^{\tau}\right) \tag{21}$$

$$\tilde{\mathfrak{B}}^{\tau} = \left(\mu_{\alpha_{\tilde{\mathfrak{B}}}}^{\tau}, \mu_{\beta_{\tilde{\mathfrak{B}}}}^{\tau}, 1-\left(1-\mu_{\gamma_{\tilde{\mathfrak{B}}}}\right)^{\tau}, 1-\left(1-\mu_{\delta_{\tilde{\mathfrak{B}}}}\right)^{\tau}, \mu_{\varepsilon_{\tilde{\mathfrak{B}}}}^{\tau}\right) \quad (22)$$

The score and accuracy values for $\tilde{\mathfrak{B}} = \left(\mu_{\alpha_{\tilde{\mathfrak{B}}}}, \mu_{\beta_{\tilde{\mathfrak{B}}}}, \mu_{\gamma_{\tilde{\mathfrak{B}}}}, \mu_{\delta_{\tilde{\mathfrak{B}}}}, \mu_{\varepsilon_{\tilde{\mathfrak{B}}}}\right)$ are calculated with Eqs. (23) and (24), respectively.

$$\mathbb{S}(\tilde{\mathfrak{B}}) = \mu_{\alpha_{\tilde{\mathfrak{B}}}} + \mu_{\beta_{\tilde{\mathfrak{B}}}} - \mu_{\gamma_{\tilde{\mathfrak{B}}}} - \mu_{\delta_{\tilde{\mathfrak{B}}}} + \mu_{\varepsilon_{\tilde{\mathfrak{B}}}} \quad (23)$$

$$\mathbb{A}(\tilde{\mathfrak{B}}) = \frac{1}{5}\left(\mu_{\alpha_{\tilde{\mathfrak{B}}}} + \mu_{\beta_{\tilde{\mathfrak{B}}}} + \mu_{\gamma_{\tilde{\mathfrak{B}}}} + \mu_{\delta_{\tilde{\mathfrak{B}}}} + \mu_{\varepsilon_{\tilde{\mathfrak{B}}}}\right) \quad (24)$$

Consensus-based Decision Matrix

Adopting a consensus or joint decision-making approach is crucial in determining the right choice. In MCDM, the optimal solution for real-world problems must be obtained through consensus. This is achieved by obtaining the decision matrix in MCDM through consensus. The aim is to obtain the decision matrix by prioritizing the evaluation matrices according to their proximity to each other. The calculation of this approach is as follows (Dinçer et al., 2025). With n criteria and m alternatives defined, evaluations are collected using a 9-point scale that are presented in Table 1.

Table 1: Linguistic variables

9-point Scale	Raw Degree
VVL	.1
VL	.2
L	.3
ML	.4
M	.5
MH	.6
H	.7
VH	.8
VVH	.9

Each linguistic evaluation is first converted to raw degree, then transformed into BLFNs in Eq. (1). Thus, evaluation matrices with the form in Eq. (25) are created from each evaluator. As many of these matrices are created as there are evaluators; that is, for e evaluators, e evaluation matrices are constructed.

$$\tilde{X}^{a} = \left[\tilde{x}_{ij}^{a}\right]_{m\times n} \quad (25)$$

Subsequently, the Euclidean distance between each pair of evaluation matrices is calculated using Eq. (26).

$$E(a,b) = \sqrt{\sum_{i=1}^{m}\sum_{j=1}^{n}\left(\mathbb{S}\left(\tilde{x}_{ij}^{a}\right) - \mathbb{S}\left(\tilde{x}_{ij}^{b}\right)\right)^{2}} \tag{26}$$

Wherein $\mathbb{S}$ is score value. Next, these distances are summed by Eq. (27).

$$T_a = \sum_{b=1}^{e} E(a,b) \tag{27}$$

Behind, the consensus values are obtained with Eq. (28).

$$\mathfrak{C}_a = \frac{1}{T_a} \tag{28}$$

Afterwards, the consensus values are normalized via Eq. (29).

$$\mathcal{N}_a = \frac{\mathfrak{C}_a}{\sum_{a=1}^{e}\mathfrak{C}_a} \tag{29}$$

After obtaining the normalized consensus values, the evaluation matrices in Eq. (25) are multiplied by these values. For this, Eq. (30) is used.

$$\tilde{Y}^{a} = \mathcal{N}_a \odot \tilde{X}^{a} \tag{30}$$

Finally, these matrices are summed by Eq. (31) for constructing the consensus-based decision matrix.

$$\widetilde{D} = \tilde{Y}^{1} \oplus \tilde{Y}^{2} \oplus \dots \oplus \tilde{Y}^{e} \tag{31}$$

Wherein $\widetilde{D} = \left[\tilde{d}_{ij}\right]_{m \times n}$ and $\tilde{d}_{ij}$ is a BLFN.

IDOCRIW-based RAM

RAM is a method that ranks alternatives without converting the cost criterion to a benefit criterion. IDOCRIW, on the other hand, is an objective method that includes two different weighting models. This approach, created by hybridizing these two methods, constructs a unique hybrid model by calculating it with BLFNs. The steps of this hybrid approach are as follows (Naz et al., 2025).

Firstly, the consensus-based decision values are defuzzified. Next, the defuzzified values are normalized using Eq. (32).

$$\mathfrak{y}_{ij} = \frac{\mathbb{S}\left(\tilde{d}_{ij}\right)}{\sum_{i=1}^{m}\mathbb{S}\left(\tilde{d}_{ij}\right)} \tag{32}$$

Subsequently, the entropies are computed with Eq. (33) and deviation rates are calculated by Eq. (34).

$$E_j = -\frac{1}{\ln m}\sum_{i=1}^{m}\mathfrak{y}_{ij}\ln\mathfrak{y}_{ij} \tag{33}$$

$$dr_j = 1 - E_j \tag{34}$$

Behind, the entropy weights are estimated via Eq. (35).

$$ew_j = \frac{dr_j}{\sum_{j=1}^{n} dr_j} \tag{35}$$

Afterwards, cost criterion is converted to benefit criterion using Eq. (36). Then, all values are normalized using Eq. (37).

$$r_{ij} = \begin{cases} \dfrac{\min \mathbb{S}(\tilde{d}_{ij})}{\mathbb{S}(\tilde{d}_{ij})} & j \in C \\ \mathbb{S}(\tilde{d}_{ij}) & j \in B \end{cases} \tag{36}$$

$$\mathfrak{z}_{ij} = \frac{r_{ij}}{\sum_{i=1}^{m} r_{ij}} \tag{37}$$

After that, square matrix is created by Eq. (38).

$$a_j = \max_i \mathfrak{z}_{ij} = a_{k_i j} \tag{38}$$

Next, relative impart loss matrix is constructed with the help of Eq. (39).

$$\mathscr{r}_{ij} = \frac{a_{jj} - a_{ij}}{a_{jj}} \tag{39}$$

In other step, the weighted system matrix is obtained via Eq. (40).

$$F = \begin{bmatrix} -\sum_{i=1}^{m} \mathscr{r}_{i1} & \cdots & \mathscr{r}_{1n} \\ \vdots & \ddots & \vdots \\ \mathscr{r}_{n1} & \cdots & -\sum_{i=1}^{m} \mathscr{r}_{in} \end{bmatrix}_{n \times n} \tag{40}$$

Behind, criterion impact loss weights are computed using Eq. (41).

$$Fq^T = 0 \tag{41}$$

In the end of IDOCRIW, the aggregate weights are calculated with Eq. (42).

$$w_j = \frac{q_j ew_j}{\sum_{j=1}^{n} (q_j ew_j)} \tag{42}$$

After criterion weights are calculated, a consensus-based decision matrix is weighted to rank the alternatives by Eq. (43).

$$\tilde{\mathscr{s}}_{ij} = w_j \odot \tilde{d}_{ij} \tag{43}$$

Subsequently, the total weighted decision values are obtained regarding to type of criterion. In other words, while the value of each benefit criterion for alternatives is summed with Eq. (44), the value of the cost criterion is summed with Eq. (45) (Sahoo and Debnath, 2025).

$$\tilde{\mathscr{s}}_i^B = \sum_{j \in B} \tilde{\mathscr{s}}_{ij} \tag{44}$$

$$\tilde{\mathscr{s}}_i^C = \sum_{j \in C} \tilde{\mathscr{s}}_{ij} \tag{45}$$

Finally, ranking scores are determined using Eq. (46).

$$rs_i = \sqrt[\left(2+\mathbb{S}\left(\tilde{s}_i^C\right)\right)]{2+\mathbb{S}\left(\tilde{s}_i^B\right)} \tag{46}$$

ANALYSIS

This section introduces the results of assessing competitive harm of ai-based pricing algorithms.

Constructing the Consensus-based Decision Matrix

The criteria are designed to align with regulation, competition law, and AI literature. The types and abbreviations of the criteria are given in Table 2.

Table 2: Types and abbreviations of criteria

Criterion	Abb	Type
Tacit Collusion Risk Level	TCRL	Cost
Price Dispersion & Dynamic Price Adjustment Intensity	PDPA	Benefit
Market Foreclosure Potential	MFPT	Cost
Consumer Welfare Impact	CWIN	Benefit
Transparency & Explainability of Pricing Algorithm	TEPA	Benefit
Data Concentration & Input Advantage	DCIA	Cost
Entry Barrier Amplification	EBAM	Cost
Regulatory Detectability	RDET	Benefit
Risk of Personalized Price Discrimination	RPPD	Cost

Five criteria are of the cost type, while four criteria are of the benefit type. AI pricing strategies are shown in Table 3. The abbreviations are also included in the same table.

Table 3: Abbreviations of AI pricing strategies

AI Pricing Strategy	Abb
Static Rule-Based Pricing Algorithms	SRBPA
Demand-Responsive Dynamic Pricing Algorithms	DRDPA
Reinforcement Learning-Based Pricing Algorithms	RLBPA
Competitor-Monitoring Pricing Algorithms	CMTPA
Personalized AI Pricing Algorithms	PAIPA
Platform-Wide Centralized Pricing Algorithms	PWCPA
Hybrid Human–AI Pricing Decision Systems	HHAIP

After the definitions are made, the evaluations are collected using the 9-point linguistic evaluation in Table 1. The linguistic evaluations are shared in Table 4.

Table 4: Linguistic evaluations

	TCRL	PDPA	MFPT	CWIN	TEPA	DCIA	EBAM	RDET	RPPD
SRBPA	ML	H	M	VH	H	M	M	H	ML
DRDPA	MH	VH	ML	H	H	MH	MH	MH	MH
RLBPA	L	H	ML	VH	H	L	L	H	L
CMTPA	MH	VH	M	H	MH	M	M	H	MH
PAIPA	MH	VH	MH	VH	H	H	H	MH	MH
PWCPA	H	VH	H	H	MH	H	H	MH	H
HHAIP	H	H	M	H	MH	M	M	M	MH
	TCRL	**PDPA**	**MFPT**	**CWIN**	**TEPA**	**DCIA**	**EBAM**	**RDET**	**RPPD**
SRBPA	M	VH	M	MH	H	M	M	MH	M
DRDPA	MH	VH	M	H	MH	ML	ML	H	M
RLBPA	ML	H	ML	VH	H	ML	ML	H	ML
CMTPA	M	H	MH	VH	MH	MH	M	MH	MH
PAIPA	MH	H	H	VH	VH	MH	H	MH	H
PWCPA	H	MH	H	H	VH	H	H	MH	MH
HHAIP	H	VH	H	H	H	ML	H	MH	ML
	TCRL	**PDPA**	**MFPT**	**CWIN**	**TEPA**	**DCIA**	**EBAM**	**RDET**	**RPPD**
SRBPA	ML	H	M	VH	H	ML	M	H	M
DRDPA	MH	VH	ML	MH	H	M	M	H	ML
RLBPA	L	VVH	ML	VH	MH	ML	L	MH	L
CMTPA	MH	VH	MH	VH	VH	MH	M	H	MH
PAIPA	MH	VH	H	H	H	M	MH	H	H
PWCPA	H	H	H	H	VH	H	H	M	H
HHAIP	MH	H	H	MH	H	MH	ML	M	H
	TCRL	**PDPA**	**MFPT**	**CWIN**	**TEPA**	**DCIA**	**EBAM**	**RDET**	**RPPD**
SRBPA	M	H	ML	VH	H	ML	M	MH	M
DRDPA	M	VH	ML	MH	MH	ML	MH	H	ML
RLBPA	L	H	L	VH	MH	L	ML	H	L
CMTPA	M	VH	MH	H	VH	MH	MH	MH	M
PAIPA	M	VH	M	H	VH	M	H	MH	M
PWCPA	MH	VH	H	H	MH	H	MH	M	MH
HHAIP	ML	H	M	H	H	ML	MH	M	MH

	TCRL	PDPA	MFPT	CWIN	TEPA	DCIA	EBAM	RDET	RPPD
SRBPA	ML	VH	ML	H	MH	M	ML	M	M
DRDPA	ML	H	M	VH	MH	MH	M	MH	ML
RLBPA	L	VVH	ML	VH	H	ML	ML	H	ML
CMTPA	MH	VH	MH	MH	H	M	M	H	M
PAIPA	H	VH	M	H	H	MH	H	MH	M
PWCPA	H	H	MH	MH	MH	H	H	MH	MH
HHAIP	H	H	H	H	MH	MH	M	MH	H

	TCRL	PDPA	MFPT	CWIN	TEPA	DCIA	EBAM	RDET	RPPD
SRBPA	M	H	M	H	H	M	M	MH	M
DRDPA	M	H	M	H	MH	M	ML	H	M
RLBPA	L	VVH	L	VH	H	ML	L	H	ML
CMTPA	M	H	M	VH	MH	M	MH	MH	M
PAIPA	MH	H	M	H	VH	H	MH	MH	M
PWCPA	H	VH	H	MH	VH	MH	H	H	MH
HHAIP	ML	VH	H	MH	H	H	ML	M	MH

	TCRL	PDPA	MFPT	CWIN	TEPA	DCIA	EBAM	RDET	RPPD
SRBPA	ML	VH	M	VH	MH	M	M	MH	ML
DRDPA	M	H	ML	MH	MH	M	M	H	M
RLBPA	ML	VH	ML	VH	MH	L	L	MH	L
CMTPA	M	VH	MH	H	VH	M	M	MH	MH
PAIPA	H	MH	H	MH	MH	MH	MH	H	MH
PWCPA	H	H	MH	MH	MH	MH	H	M	MH
HHAIP	M	VH	ML	H	MH	H	ML	M	H

	TCRL	PDPA	MFPT	CWIN	TEPA	DCIA	EBAM	RDET	RPPD
SRBPA	M	H	ML	VH	MH	ML	M	MH	ML
DRDPA	ML	H	ML	VH	H	ML	M	H	MH
RLBPA	ML	H	L	H	MH	ML	ML	MH	ML
CMTPA	M	H	MH	VH	VH	MH	MH	MH	M
PAIPA	H	MH	H	MH	MH	H	MH	MH	H
PWCPA	H	H	H	MH	MH	H	MH	MH	H
HHAIP	H	MH	MH	MH	MH	MH	ML	MH	MH

	TCRL	PDPA	MFPT	CWIN	TEPA	DCIA	EBAM	RDET	RPPD
SRBPA	M	VH	ML	H	H	M	M	M	ML
DRDPA	M	H	MH	MH	MH	M	M	H	MH
RLBPA	ML	VH	ML	VH	H	ML	ML	MH	ML
CMTPA	M	H	M	MH	MH	M	MH	MH	M
PAIPA	H	MH	M	VH	VH	H	M	MH	H

PWCPA	MH	H	H	MH	MH	MH	H	H	MH
HHAIP	ML	MH	M	MH	H	MH	M	M	H
	TCRL	**PDPA**	**MFPT**	**CWIN**	**TEPA**	**DCIA**	**EBAM**	**RDET**	**RPPD**
SRBPA	M	VH	M	H	MH	ML	ML	M	M
DRDPA	M	H	ML	VH	H	MH	MH	H	ML
RLBPA	ML	H	L	VH	VH	ML	L	H	ML
CMTPA	M	H	MH	MH	MH	MH	MH	MH	MH
PAIPA	H	VH	M	H	VH	MH	M	H	MH
PWCPA	H	MH	MH	MH	H	MH	MH	MH	H
HHAIP	H	VH	ML	MH	H	H	M	M	MH

Linguistic evaluations in Table 4 are converted to raw belonging degrees. In other words, for M, it is .5. Next, the BLFNs are calculated according to Eqs. (1) – (18). For example, BLFN for .5 equals to $\left(e^{.5-1}, \frac{1}{1+e^{-10(.5-.5)}}, e^{-\frac{.5^2}{2}}, e^{-.5}, -e^{-\frac{.5^2}{2}}+1\right) = (.607, .500, .000, .607, 1.000)$. Then, these BLFNs are defuzzified using score values. For example, the defuzzified values of M is $.607 + .500 - .000 - .607 + 1.000 = 1.500$. In this way, defuzzified values of all linguistic evaluations are obtained. After that, the Euclidean distance between each pair of evaluation matrices is calculated using Eq. (26). The distance matrix is illustrated in Table 5.

Table 5: Distance matrix

	EM1	**EM2**	**EM3**	**EM4**	**EM5**	**EM6**	**EM7**	**EM8**	**EM9**	**EM10**
EM1		2.303	2.015	2.356	2.123	2.337	2.062	2.248	2.362	2.235
EM2	2.303		2.368	2.515	2.532	2.503	2.810	2.475	2.687	2.663
EM3	2.015	2.368		2.308	2.251	2.233	1.965	2.190	2.661	2.369
EM4	2.356	2.515	2.308		2.476	2.403	2.401	2.587	2.484	2.560
EM5	2.123	2.532	2.251	2.476		2.121	2.286	2.268	2.346	2.103
EM6	2.337	2.503	2.233	2.403	2.121		2.247	2.342	1.833	2.328
EM7	2.062	2.810	1.965	2.401	2.286	2.247		2.014	2.164	2.167
EM8	2.248	2.475	2.190	2.587	2.268	2.342	2.014		2.275	2.339
EM9	2.362	2.687	2.661	2.484	2.346	1.833	2.164	2.275		2.294
EM10	2.235	2.663	2.369	2.560	2.103	2.328	2.167	2.339	2.294	

Next, the sum of each row of the distance matrix is calculated by Eq. (27). The total distances are displayed in Table 6.

Table 6: Total distances

	Total
EM1	42.898
EM2	43.216

EM3	42.449
EM4	42.597
EM5	40.856
EM6	40.464
EM7	40.854
EM8	41.846
EM9	42.165
EM10	21.058

Behind, the consensus values are obtained with Eq. (28). Afterwards, the consensus values are normalized via Eq. (29). The results are summarized in Table 7.

Table 7: Consensus and normalized values

	Consensus	Normalized Consensus
EM1	.023	.089
EM2	.023	.088
EM3	.024	.090
EM4	.023	.090
EM5	.024	.093
EM6	.025	.094
EM7	.024	.093
EM8	.024	.091
EM9	.024	.090
EM10	.047	.181

Finally, the evaluation matrices are multiplied by these values and summed using Eqs. (30) and (31). For example, first evaluation matrix's first element is multiplied by .089 as $\left((1-(1-.549)^{.89}),(1-(1-.269)^{.089}),.000^{.089},.670^{.089},(1-(1-1.00)^{.089})\right)$. The all these fuzzy values are summed. The consensus-based decision matrix is shared in Table 8.

Table 8: Consensus-based decision matrix

	TCRL	PDPA	MFPT	CWIN	TEPA	DCIA	EBAM	RDET	RPPD
SRBPA	(.586,.426,0,.629,1)	(.787,.928,0,.47,1)	(.586,.426,0,.629,1)	(.775,.916,0,.479,1)	(.711,.827,0,.52,1)	(.581,.406,0,.635,1)	(.591,.445,0,.623,1)	(.663,.708,0,.559,1)	(.586,.426,0,.629,1)
DRDPA	(.615,.546,0,.602,1)	(.772,.914,0,.479,1)	(.578,.399,0,.64,1)	(.752,.886,0,.496,1)	(.704,.814,0,.525,1)	(.617,.558,0,.601,1)	(.621,.571,0,.596,1)	(.729,.862,0,.506,1)	(.601,.498,0,.618,1)

RLBPA	(.526,.204,.002,.702,.998)	(.816,.94,0,.461,1)	(.526,.204,.002,.702,.998)	(.813,.948,0,.453,1)	(.735,.864,0,.506,1)	(.535,.231,.001,.689,.999)	(.521,.19,.002,.708,.998)	(.717,.84,0,.515,1)	(.531,.218,.001,.695,.999)
CMTPA	(.625,.578,0,.59,1)	(.78,.922,0,.475,1)	(.654,.681,0,.564,1)	(.752,.885,0,.497,1)	(.741,.867,0,.506,1)	(.642,.642,0,.575,1)	(.643,.644,0,.574,1)	(.691,.784,0,.534,1)	(.642,.643,0,.575,1)
PAIPA	(.707,.818,0,.524,1)	(.772,.91,0,.483,1)	(.667,.719,0,.559,1)	(.754,.892,0,.492,1)	(.777,.916,0,.479,1)	(.688,.777,0,.539,1)	(.683,.763,0,.544,1)	(.698,.8,0,.529,1)	(.682,.762,0,.544,1)
PWCPA	(.729,.862,0,.506,1)	(.749,.885,0,.496,1)	(.717,.839,0,.515,1)	(.697,.799,0,.53,1)	(.732,.855,0,.51,1)	(.711,.827,0,.52,1)	(.717,.84,0,.515,1)	(.669,.726,0,.554,1)	(.704,.814,0,.525,1)
HHAIP	(.679,.759,0,.554,1)	(.77,.909,0,.483,1)	(.655,.69,0,.574,1)	(.704,.814,0,.524,1)	(.717,.839,0,.515,1)	(.676,.749,0,.553,1)	(.607,.521,0,.613,1)	(.625,.578,0,.59,1)	(.69,.782,0,.538,1)

Weighting of Criteria

Firstly, the consensus-based decision values are defuzzified. The defuzzified values are exhibited in Table 9.

Table 9: Defuzzified values

	TCRL	PDPA	MFPT	CWIN	TEPA	DCIA	EBAM	RDET	RPPD
SRBPA	1.383	2.245	1.383	2.212	2.018	1.353	1.413	1.812	1.383
DRDPA	1.559	2.207	1.336	2.141	1.993	1.574	1.597	2.085	1.481
RLBPA	1.025	2.295	1.025	2.308	2.093	1.076	.999	2.042	1.051
CMTPA	1.612	2.227	1.771	2.140	2.103	1.710	1.712	1.942	1.710
PAIPA	2.001	2.198	1.827	2.153	2.214	1.926	1.901	1.969	1.900
PWCPA	2.086	2.137	2.041	1.967	2.077	2.017	2.042	1.841	1.993
HHAIP	1.884	2.196	1.770	1.994	2.041	1.871	1.515	1.613	1.933

Next, the normalized values are estimated using Eq. (32). The normalized matrix is expressed in Table 10.

Table 10: Normalized matrix

	TCRL	PDPA	MFPT	CWIN	TEPA	DCIA	EBAM	RDET	RPPD
SRBPA	.120	.145	.124	.148	.139	.117	.126	.136	.121
DRDPA	.135	.142	.120	.144	.137	.137	.143	.157	.129
RLBPA	.089	.148	.092	.155	.144	.093	.089	.153	.092
CMTPA	.140	.144	.159	.143	.145	.148	.153	.146	.149
PAIPA	.173	.142	.164	.144	.152	.167	.170	.148	.166
PWCPA	.181	.138	.183	.132	.143	.175	.183	.138	.174
HHAIP	.163	.142	.159	.134	.140	.162	.136	.121	.169

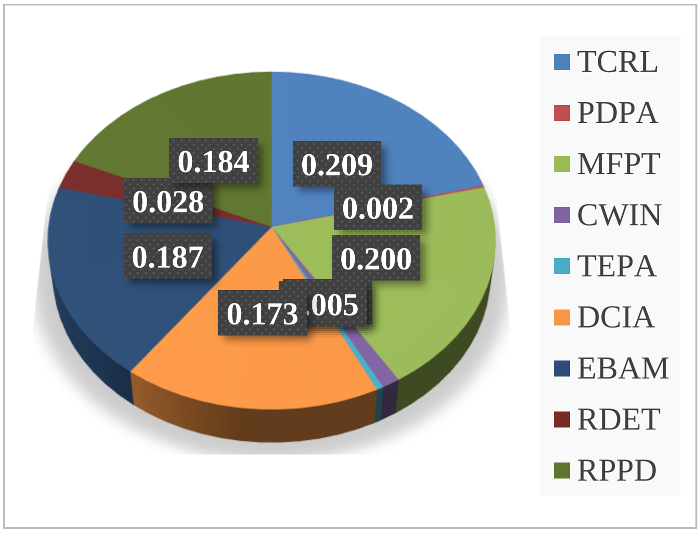
Subsequently, the entropies and deviation rates are computed with Eqs. (33) and (34), respectively. These results are displayed in Table 11.

Table 11: Entropy and deviation rate

	TCRL	PDPA	MFPT	CWIN	TEPA	DCIA	EBAM	RDET	RPPD
Entropy	.988	1.000	.989	.999	1.000	.990	.989	.998	.990
Deviation rate	.012	.000	.011	.001	.000	.010	.011	.002	.010

Behind, the deviation rates are normalized via Eq. (35). Thus, the entropy weights are obtained. The weights by entropy method are presented in Figure 2.

Figure 2: Entropy weights of criteria



Afterwards, cost criterion is converted to benefit criterion using Eq. (36). Then, all values are normalized using Eq. (37). The results are given in Table 12.

Table 12: Normalized values of benefited matrix

	TCRL	PDPA	MFPT	CWIN	TEPA	DCIA	EBAM	RDET	RPPD
SRBPA	.162	.145	.157	.148	.139	.167	.154	.136	.161
DRDPA	.143	.142	.162	.144	.137	.143	.136	.157	.151
RLBPA	.218	.148	.211	.155	.144	.209	.218	.153	.212
CMTPA	.139	.144	.122	.143	.145	.132	.127	.146	.131

PAIPA	.112	.142	.119	.144	.152	.117	.114	.148	.118
PWCPA	.107	.138	.106	.132	.143	.112	.107	.138	.112
HHAIP	.119	.142	.122	.134	.140	.120	.144	.121	.115

After that, square matrix is created by Eq. (38). The maximum value of the j-th criterion is selected as the j-th row and j-th column element of the square matrix. Then, the square matrix is completed with the row values of the normalized values corresponding to this maximum value. This matrix is shared in Table 13.

Table 13: Square matrix

	TCRL	PDPA	MFPT	CWIN	TEPA	DCIA	EBAM	RDET	RPPD
TCRL	.218	.148	.211	.155	.144	.209	.218	.153	.212
PDPA	.218	.148	.211	.155	.144	.209	.218	.153	.212
MFPT	.218	.148	.211	.155	.144	.209	.218	.153	.212
CWIN	.218	.148	.211	.155	.144	.209	.218	.153	.212
TEPA	.112	.142	.119	.144	.152	.117	.114	.148	.118
DCIA	.218	.148	.211	.155	.144	.209	.218	.153	.212
EBAM	.218	.148	.211	.155	.144	.209	.218	.153	.212
RDET	.143	.142	.162	.144	.137	.143	.136	.157	.151
RPPD	.218	.148	.211	.155	.144	.209	.218	.153	.212

Next, relative impact loss matrix is constructed with the help of Eq. (39). The relative impact loss matrix is expressed in Table 14.

Table 14: Relative impact loss matrix

	TCRL	PDPA	MFPT	CWIN	TEPA	DCIA	EBAM	RDET	RPPD
TCRL	.000	.000	.000	.000	.054	.000	.000	.021	.000
PDPA	.000	.000	.000	.000	.054	.000	.000	.021	.000
MFPT	.000	.000	.000	.000	.054	.000	.000	.021	.000
CWIN	.000	.000	.000	.000	.054	.000	.000	.021	.000
TEPA	.488	.042	.439	.067	.000	.442	.475	.056	.447
DCIA	.000	.000	.000	.000	.054	.000	.000	.021	.000
EBAM	.000	.000	.000	.000	.054	.000	.000	.021	.000
RDET	.343	.039	.233	.072	.100	.317	.374	.000	.290
RPPD	.000	.000	.000	.000	.054	.000	.000	.021	.000

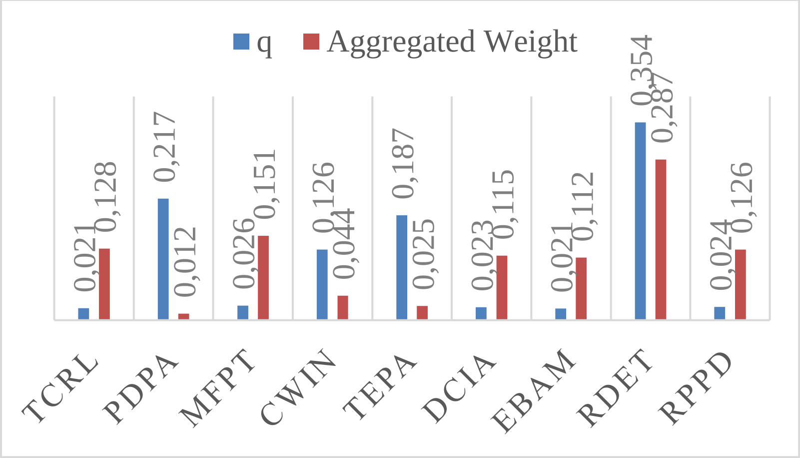
In other step, the weighted system matrix is obtained via Eq. (40). This weighted system matrix is exhibited in Table 15.

Table 15: Weighted system matrix

	TCRL	PDPA	MFPT	CWIN	TEPA	DCIA	EBAM	RDET	RPPD
TCRL	-.830	.000	.000	.000	.054	.000	.000	.021	.000
PDPA	.000	-.081	.000	.000	.054	.000	.000	.021	.000
MFPT	.000	.000	-.672	.000	.054	.000	.000	.021	.000
CWIN	.000	.000	.000	-.139	.054	.000	.000	.021	.000
TEPA	.488	.042	.439	.067	-.480	.442	.475	.056	.447
DCIA	.000	.000	.000	.000	.054	-.758	.000	.021	.000
EBAM	.000	.000	.000	.000	.054	.000	-.849	.021	.000
RDET	.343	.039	.233	.072	.100	.317	.374	-.202	.290
RPPD	.000	.000	.000	.000	.054	.000	.000	.021	-.737

Behind, criterion impact loss weights and the aggregate weights are calculated using Eq. (41). The results are visualized in Figure 3.

Figure 3: Q and aggregate weights



According to aggregate weights in Figure 3, the most important criteria are regulatory detectability with .287 and market foreclosure potential with .151.

Ranking of AI Pricing Strategies

After criterion aggregate weights are calculated, a consensus-based decision matrix is weighted by Eq. (43). In other words, the elements in Table 8 are multiplied by aggregate weights in Figure 3. For example, first element is established as $((1-(1-.586)^{.128}),(1-(1-.426)^{.128}),.000^{.128},.629^{.128},1^{.128})$. The weighted decision matrix is illustrated in Table 16.

Table 16: Weighted decision matrix

	TCRL	PDPA	MFPT	CWIN	TEPA	DCIA	EBAM	RDET	RPPD
SRBPA	(.107,.068,.25,.943,.75)	(.018,.03,.715,.991,.284)	(.125,.08,.194,.932,.805)	(.063,.102,.303,.968,.696)	(.031,.043,.581,.984,.419)	(.096,.058,.299,.949,.7)	(.095,.064,.284,.949,.715)	(.268,.298,.007,.846,.993)	(.105,.068,.254,.943,.746)
DRDPA	(.115,.096,.187,.937,.813)	(.017,.028,.727,.991,.272)	(.122,.074,.216,.935,.783)	(.059,.09,.337,.97,.662)	(.03,.042,.589,.984,.41)	(.105,.09,.216,.943,.783)	(.103,.09,.217,.944,.782)	(.313,.434,.001,.822,.999)	(.109,.083,.221,.941,.778)
RLBPA	(.091,.029,.441,.956,.558)	(.02,.032,.701,.991,1)	(.106,.034,.381,.948,.618)	(.071,.122,.254,.966,.745)	(.033,.049,.553,.983,.447)	(.085,.03,.444,.958,.556)	(.079,.023,.506,.962,.493)	(.304,.409,.002,.826,.998)	(.091,.031,.427,.955,.572)
CMTPA	(.118,.104,.167,.935,.832)	(.018,.029,.721,.991,.278)	(.148,.158,.083,.917,.916)	(.059,.09,.337,.97,.662)	(.034,.05,.55,.983,.449)	(.112,.112,.168,.938,.832)	(.109,.109,.177,.94,.823)	(.287,.357,.003,.835,.997)	(.122,.122,.142,.932,.857)
PAIPA	(.145,.196,.068,.921,.932)	(.017,.028,.731,.992,.269)	(.153,.174,.073,.916,.926)	(.059,.093,.331,.97,.669)	(.037,.061,.501,.982,.499)	(.126,.159,.107,.931,.893)	(.121,.149,.121,.934,.878)	(.291,.37,.003,.833,.997)	(.135,.166,.093,.926,.906)
PWCPA	(.154,.224,.051,.917,.949)	(.016,.025,.748,.992,.251)	(.173,.241,.036,.905,.964)	(.051,.068,.411,.973,.588)	(.033,.048,.56,.983,.44)	(.133,.183,.084,.927,.916)	(.132,.185,.084,.928,.916)	(.272,.311,.006,.844,.994)	(.142,.191,.071,.922,.928)
HHAIP	(.135,.166,.097,.927,.903)	(.017,.028,.731,.992,.268)	(.148,.162,.087,.92,.912)	(.052,.071,.4,.972,.599)	(.031,.045,.572,.983,.427)	(.122,.147,.124,.934,.876)	(.099,.079,.25,.947,.749)	(.246,.219,.018,.859,.982)	(.137,.175,.085,.925,.914)

Subsequently, the weighted decision values are summed regarding to type of criterion with Eqs. (44) and (45), respectively. The results are summarized in Table 17.

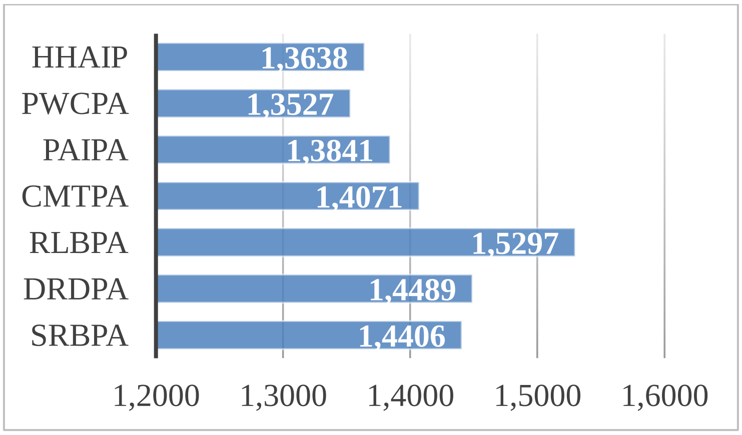
Table 17: Total weighted decision values

	$\tilde{s}_i^B$	$\tilde{s}_i^C$

SRBPA	(.348,.416,.001,.799,.999)	(.428,.296,.001,.746,.999)
DRDPA	(.384,.52,0,.778,1)	(.444,.364,0,.734,1)
RLBPA	(.387,.522,0,.778,1)	(.377,.138,.016,.797,.984)
CMTPA	(.363,.46,0,.789,1)	(.477,.476,0,.705,1)
PAIPA	(.369,.478,0,.786,1)	(.518,.603,0,.679,1)
PWCPA	(.343,.403,.001,.8,.999)	(.549,.683,0,.658,1)
HHAIP	(.319,.327,.003,.815,.997)	(.497,.547,0,.697,1)

Finally, ranking scores are determined using Eq. (46). The ranking score for each AI pricing strategy are shown in Figure 4.

Figure 4: Ranking scores of AI pricing strategies



When Figure 4 is examined, the most appropriate ai pricing strategies are reinforcement learning-based pricing algorithms with 1.5297 and demand-responsive dynamic pricing algorithms with 1.4489.

Sensitivity Analysis

Sensitivity analysis is needed to ensure the robustness of the results. This involves comparing ranking results by minimally altering the weight of a criterion. Secondly, scenarios are constructed using Monte Carlo simulation based on the original criterion weights, and rankings are compared. Finally, the similarity between the results and other different ranking models in the literature is examined. First, the weight of each criterion is changed by 10%. In other words, the weight of one criterion is increased or decreased by 10%, while the weights of the other criteria remain constant. RAM analyses are performed with the updated weights. Despite the minimal change in criterion weights, the ranking results of the AI pricing strategies are shared in Table 18.

Table 18: Ranking results by minimal changing of criteria

	TCRL +10%	**PDPA +10%**	**MFPT +10%**	**CWIN +10%**	**TEPA +10%**	**DCIA +10%**	**EBAM +10%**	**RDET +10%**	**RPPD +10%**	**TCRL - 10%**	**PDPA - 10%**	**MFPT - 10%**	**CWIN - 10%**	**TEPA - 10%**	**DCIA - 10%**	**EBAM - 10%**	**RDET - 10%**	**RPPD - 10%**
SRBPA	1.438	1.442	1.438	1.443	1.44	1.439	1.439	1.45	1.4384	1.444	1.44	1.444	1.439	1.44	1.44	1.443	1.431	1.444
DRDPA	1.446	1.45	1.447	1.451	1.45	1.447	1.447	1.46	1.4467	1.452	1.449	1.452	1.448	1.448	1.45	1.452	1.438	1.452
RLBPA	1.527	1.531	1.526	1.533	1.53	1.527	1.527	1.542	1.5269	1.533	1.529	1.534	1.528	1.529	1.53	1.533	1.518	1.534
CMTPA	1.405	1.408	1.404	1.409	1.41	1.405	1.405	1.416	1.405	1.41	1.407	1.411	1.406	1.407	1.41	1.41	1.398	1.41
PAIPA	1.382	1.385	1.382	1.386	1.39	1.382	1.382	1.393	1.3821	1.387	1.384	1.387	1.383	1.383	1.39	1.386	1.376	1.387
PWCPA	1.351	1.353	1.351	1.354	1.35	1.351	1.351	1.361	1.3511	1.355	1.353	1.356	1.352	1.352	1.35	1.355	1.345	1.355
HHAIP	1.362	1.365	1.362	1.366	1.37	1.362	1.363	1.372	1.3616	1.367	1.364	1.367	1.362	1.363	1.37	1.366	1.356	1.367

When Table 18 is examined, the ranking of AI pricing strategies remains constant, despite minimal changes in weights. This is one of the factors indicating the robustness of the results. In the second stage, twenty scenarios are constructed using Monte Carlo simulation. The criterion weights for the twenty scenarios are summarized in Table 19.

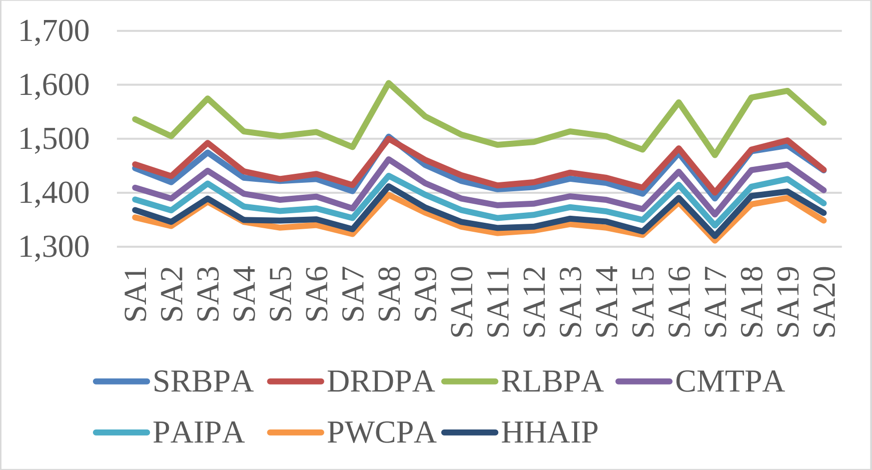
Table 19: Weights for scenarios

	TCRL	**PDPA**	**MFPT**	**CWIN**	**TEPA**	**DCIA**	**EBAM**	**RDET**	**RPPD**
SA1	.095	.007	.159	.071	.012	.113	.134	.282	.126
SA2	.142	.009	.156	.023	.026	.115	.103	.279	.146
SA3	.084	.006	.152	.025	.012	.100	.075	.395	.150
SA4	.150	.011	.123	.014	.031	.141	.052	.298	.180
SA5	.138	.006	.182	.067	.036	.086	.117	.217	.152
SA6	.159	.008	.191	.047	.020	.087	.108	.267	.114
SA7	.090	.006	.223	.040	.017	.092	.126	.240	.166
SA8	.150	.015	.085	.125	.036	.116	.076	.280	.117
SA9	.121	.004	.172	.038	.056	.124	.066	.291	.129
SA10	.141	.002	.205	.050	.019	.088	.083	.264	.147

SA11	.192	.007	.146	.038	.015	.150	.120	.249	.081
SA12	.124	.003	.142	.040	.021	.093	.117	.254	.206
SA13	.121	.003	.194	.045	.024	.068	.116	.273	.156
SA14	.113	.007	.162	.042	.010	.109	.162	.273	.122
SA15	.148	.003	.180	.027	.029	.088	.108	.240	.176
SA16	.101	.015	.110	.022	.055	.147	.073	.336	.140
SA17	.189	.011	.229	.036	.006	.062	.109	.226	.132
SA18	.180	.012	.071	.078	.018	.061	.142	.318	.120
SA19	.133	.007	.123	.053	.037	.090	.091	.354	.113
SA20	.126	.003	.106	.095	.014	.092	.151	.246	.168

RAM analyses are applied using these scenario weights. This allows us to see how AI pricing strategies perform in response to changes in criterion priority status, just as in the real world. The simulation results are visualized in Figure 5.

Figure 5: Ranking by Monte Carlo



As can be seen in Figure 5, the ranking of AI pricing strategies remains unchanged as a result of the simulation analysis. Finally, the results calculated using different ranking models in the literature are compared. In this context, the ARAS and TOPSIS methods, which transform the cost criterion, and the WISP method, which evaluates cost and benefit criteria separately, such as RAM, are preferred. ARAS, TOPSIS, and WISP results are presented in Table 20.

Table 20: ARAS, TOPSIS and WISP results

	ARAS	TOPSIS	WISP
SRBPA	.791	.614	.923
DRDPA	.782	.599	.925
RLBPA	.994	.965	1.000
CMTPA	.708	.391	.890
PAIPA	.667	.283	.869
PWCPA	.624	.163	.845
HHAIP	.647	.241	.857

Table 20 shows that the RAM results are like the ranking results of the three methods. The Pearson correlation coefficients between the methods and RAM are .991, .996, and .999, respectively. A high correlation coefficient indicates the reliability of the results.

CONCLUSION

This study aimed to identify priority strategies to mitigate the negative competitive effects of AI based pricing algorithms in digital markets. The analysis results clearly indicate that reinforcement learning based pricing algorithms and static rule-based pricing algorithms emerge as the most critical strategies. This study is subject to several theoretical and methodological limitations. From a theoretical perspective, the model relies on a predefined set of criteria and strategies derived from the current literature, which may not fully capture emerging forms of algorithmic pricing or future market dynamics. The proposed decision model also depends on expert judgments, which, although systematically processed, inevitably reflect subjective perspectives and contextual knowledge. In addition, the behavioral leadership fuzzy sets, while offering originality and depth, introduce complexity that may limit immediate applicability in large scale regulatory settings. Future research could address these limitations by expanding the expert pool, incorporating cross country comparisons, and validating the model with empirical market data.

REFERENCES

Abada, I., Lambin, X., & Tchakarov, N. (2024). Collusion by mistake: Does algorithmic sophistication drive supra-competitive profits? *European Journal of Operational Research, 318*(3), 927–953. https://doi.org/10.1016/j.ejor.2024.06.006

An, L. (2025). Legal controls on big data price discrimination for existing customers. *International Journal of Digital Crime and Forensics*, 17(1). https://doi.org/10.4018/IJDCF.372895

Assad, S., Clark, R., Ershov, D., & Xu, L. (2024). Algorithmic pricing and competition: Empirical evidence from the German retail gasoline market. *The Review of Economic Studies*, *91*(3), 1271–1311. https://doi.org/10.1093/restud/rdad075

Baskaran, S. (2025). Revisiting exploitative abuses in digital platform markets. *Journal of Antitrust Enforcement, 13*(2), 265–283. https://doi.org/10.1093/jaenfo/jnae050

Bichler, M., Durmann, J., & Oberlechner, M. (2025). Algorithmic pricing and algorithmic collusion. *Business & Information Systems Engineering*, *67*(6), 971–979. https://doi.org/10.1007/s12599-025-00965-z

Birch, K., & Adediji, 'Damola. (2025). Undermining competition, undermining markets? Implications of Big Tech and digital personal data for competition policy. *Big Data & Society*, *12*(1). https://doi.org/10.1177/20539517241311584

Brown, Z. Y., & MacKay, A. (2023). Competition in pricing algorithms. *American Economic Journal: Microeconomics, 15*(2), 109–156. https://doi.org/10.1257/mic.20210158

Buckley, P. J., Elia, S., Gaur, A., Krakowski, S., Kuivalainen, O., & Pedota, M. (2025). Artificial intelligence and international business: Theoretical challenges, strategic implications, and research agenda. *Journal of World Business*. https://doi.org/10.1016/j.jwb.2025.101710

Carissimo, C., Falniowski, F., Rahimi, S., & Nax, H. H. (2025). *Algorithmic collusion is algorithm orchestration*. arXiv preprint arXiv:2508.14766. [Forthcoming in *Games and Economic Behavior*].

Cartea, Á., Chang P., Penalva J., Waldon, H., (2026). Algorithmic collusion and a folk theorem from learning with bounded rationality, *Games and Economic Behavior*, *157*, 1–21. https://doi.org/10.1016/j.geb.2025.11.012

Csurgai-Horváth, G. (2024). Regulating algorithmic bias as a key element of digital market regulation, *World Competition*, Issue, *47*(2), 193-212. https://kluwerlawonline.com/journalarticle/World+Competition/47.2/WOCO2024015

Cui, S. (2025). Increased (platform) competition reduces (seller) competition. *The Journal of Industrial Economics*, *73*(2), 285-315. https://doi.org/10.1111/joie.12409

D'Amico, E., Belitski, M., Braga, A., & Savoie, R. (2025). Enhancing knowledge spillover of innovation through artificial intelligence: An empirical investigation. *The Journal of Technology Transfer*. https://doi.org/10.1007/s10961-025-10217-7

Dinçer, H., Yüksel, S., Eti, S., & Ergün, E. (2025). Predictive expert assessments for large-scale battery storage system investments with conditional multi-facet fuzzy logarithmic least-squares and orthogonal metric robust aggregation. *Scientific Reports*. https://doi.org/10.1038/s41598-025-32750-z

Dou, L., & Dou, X. (2025). Towards just AI: Challenges and solution framework for algorithmic discrimination in judicial system. *International Journal of Digital Law and Governance*, *2*(1), 39–81. https://doi.org/10.1515/ijdlg-2024-0020

Erdmann, A., Yazdani, M., Mas Iglesias, J. M., & Marin Palacios, C. (2024). Pricing powered by artificial intelligence: An assessment model for the sustainable implementation of AI supported price functions. *Informatica, 35*(3), 529–556. https://doi.org/10.15388/24-INFOR559

Gülen Ertosun, Ö., Yüksel, S., Eti, S., & Dinçer, H. (2026). Understanding the psychology of sustainability through behavioral leadership fuzzy decision-making on employee motivation. *Discover Sustainability*. https://doi.org/10.1007/s43621-025-02529-3

Hutchinson, C. S. (2022). Potential abuses of dominance by big tech through their use of Big Data and AI. *Journal of Antitrust Enforcement, 10*(3), 443–468. https://doi.org/10.1093/jaenfo/jnac004

Kadner-Graziano, A. S. (2025). Vertical mergers without foreclosure. *Journal of Economics & Management Strategy*, *34*(2), 593-611. https://doi.org/10.1111/jems.12611

Lambin, Xavier & Raizonville, Adrien, (2025). From black box to glass box: algorithmic explainability as a strategic decision. *Information Economics and Policy*, *71*. https://doi.org/10.1016/j.infoecopol.2025.101149.

Ma, Y., Guo, X., Su, W., & Fu, G. (2024). The evolution of price discrimination in e-commerce platform trading: A perspective of platform corporate social responsibility. *Journal of Theoretical and Applied Electronic Commerce Research, 19*(3), 1907–1921. https://doi.org/10.3390/jtaer19030094

Majumdar, R., Gurtoo, A., & Maileckal, M. (2025). Developing a data pricing framework for data exchange. *Future Business Journal, 11*, Article 4. https://doi.org/10.1186/s43093-025-00422-z

Manne, G. A., Radic, L., & Auer, D. (2025). Regulate for what? A closer look at the rationale and goals of digital competition regulations. *Berkeley Business Law Journal, 22*(1), 201–263.

Mao, Q., & Xu, M. (2025). Navigating the ethical landscape of ai innovation: challenges and opportunities. *International Journal of Digital Law and Governance*, *2*(1), 197–221. https://doi.org/10.1515/ijdlg-2025-0005

Marty, F., & Warin, T. (2025). Deciphering algorithmic collusion: Insights from bandit algorithms and implications for antitrust enforcement. *Journal of Economy and Technology, 3*, 34–43. https://doi.org/10.1016/j.ject.2024.10.001

Mihet, R., Rishabh, K., & Gomes, O. (2026). Is it AI or data that drives firm market power? *Journal of Monetary Economics*, *157*, https://doi.org/10.1016/j.jmoneco.2025.103878

Naz, S., Fatima, S. S., Butt, S. A., Majeed, M., & Fatima, A. (2025). A novel MAGDM approach for software quality assessment: A focus on Microsoft DevOps Transformation using 2-Tuple Linguistic Single-valued Neutrosophic set. In: Smarandache, F., Khan, Z. (eds) *Neutrosophic Paradigms: Advancements in Decision Making and Statistical Analysis: Neutrosophic Principles for Handling Uncertainty*, *435,* 403-432. Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-78505-4_21.

O'Reilly, T., Strauss, I., & Mazzucato, M. (2024). Algorithmic attention rents: A theory of digital platform market power. *Data & Policy*, *6*, e6. https://doi.org/10.1017/dap.2024.1

OECD. (2023). *Algorithmic Competition: OECD Competition Policy Roundtable Background Note*. OECD. https://www.oecd.org/daf/competition/algorithmic-competition-2023.pdf.

Peng, G., Zhang, X. & Liu, Y. (2024). Ex-post vs. ex-ante regulation on platforms' discriminatory pricing under different market structures: an evolutionary game study. *Electron Commer Res, 26, 319–350.* https://doi.org/10.1007/s10660-024-09933-3

Sahoo, B., & Debnath, B. K. (2025). An integrated Pythagorean Fuzzy Group Decision-Making Framework for sustainable biomass power plant site selection in rural communities. *Energy for Sustainable Development*, *89*, 101868. https://doi.org/10.1016/j.esd.2025.101868.

Spann, M., Bertini, M., Koenigsberg, O., Zeithammer, R., Aparicio, D., Chen, Y., Fantini, F., Jin, G. Z., Morwitz, V. G., Popkowski Leszczyc, P., Vitorino, M. A., Williams, G. Y., & Yoo, H. (2025). Algorithmic pricing: Implications for marketing strategy and regulation. *International Journal of Research in Marketing*. https://doi.org/10.1016/j.ijresmar.2025.05.001

Wibowo, K. P., Munakit, D. A., Gunawan, W., Majid, Q. A., Nirwan, N. I., & Ohoira, M. C. B. (2025). Digital antitrust: Reimagining competition law for platform economies and AI-driven markets. *Journal of Posthumanism,* *5*(6), 1050–1066. https://doi.org/10.63332/joph.v5i6.2178