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Big Data Analytics Algorithms for Dynamic Pricing: The Legal Analysis of the Indonesia Competitions Law readiness in Digital Era

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Abstract

This article analyzes the readiness of Indonesian competition law regarding the utilization of big data and reinforcement learning as tools to improve retailers' pricing strategies, ultimately leading to increased profitability and higher customer engagement and loyalty. It conducts a comprehensive review of scholarly literature pertaining to adaptive algorithmic pricing, with a specific focus on analyzing trends and the impacts of algorithmic pricing strategies. The literature review spans the years 2018 to 2022 and adheres to PRISMA criteria, with academic journals from Scopus serving as the primary source of research papers. The findings of this review indicate that it is evident that the most frequently utilized type of algorithm RL which shares a resemblance to human learning processes. Competition law enforcement should consider the possibility of illicit agreements between these artificial agents of colluding companies. In light of the capacity of EAs to facilitate the coordination of illicit agreements, it is imperative to consider the reformulation of Article 5 of Law Number 5 of 1999 and Regulation of KPPU Number 4 of 2011, particularly regarding the classification of price-fixing, to be adjusted to the latest developments, particularly regarding "EAs". ITE Law also should not be limited to EAs merely acting as "tools". Instead, it should acknowledge their capacity to function as "AI agents" capable of autonomous action.

Keywords: Algorithmic Pricing; Dynamic Pricing; Legal Analysis

1. INTRODUCTION

The term "pricing strategies algorithm," abbreviated as APS, encompasses the methodologies and techniques employed by companies to establish the pricing structures for their products or services. This process encompasses a multitude of considerations, including production costs, market demand, competitive forces, profit objectives, and customer inclinations.[1] APS, known as the pricing strategies algorithm, plays a pivotal role in assisting companies in determining the most advantageous pricing structures to attain their desired business objectives.[2] Its

1 Sungwoo Choi, Myungkeun Song, and Luo Jing, "Let Your Algorithm Shine: The Impact of Algorithmic Cues on Consumer Perceptions of Price Discrimination," *Tourism Management* 99 (December 2023): 104792, https://doi.org/10.1016/j.tourman.2023.104792.

2 Haiyan Song and Gang Li, "Tourism Demand Modelling and Forecasting—A Review of Recent Research," *Tourism Management* 29, no. 2 (April 2008): 203–20, https://doi.org/10.1016/j.tour-

 DOI: http://dx.doi.org/10.29303/v12i1.1303

application spans various business domains with the primary aim of achieving several favorable business outcomes. APS increases business earnings tremendously. Firstly, Pricing algorithms let companies optimize revenue by fine-tuning product prices. These algorithms allow companies to calculate manufacturing costs, demand, and client preferences to provide competitive pricing. APS helps organizations evaluate market competitiveness and set profitable pricing strategies.[3] Secondly, APS helps companies adjust their pricing in competitive markets. Firms can use competitors' pricing methods, market data, and intelligent pricing to choose price points that provide them with a competitive edge and a large market share.[4] Thirdly, pricing methods and algorithms optimize capacity use in businesses with limited capacity, such as transportation and hotels. Companies can dynamically modify prices based on demand to maximize revenue and minimize capacity gaps and underutilization.[5]

AI and big data are crucial to APS advancement, as noted. Big data includes complex datasets from sales transactions, customer records, market data, and other sources. Big data gives firm deep insights into customer behavior, market trends, and price factors. It also helps organizations perform more accurate statistical analysis of past and current data. Pricing algorithms can use large amounts of historical data to predict patterns. This helps firms optimize pricing by taking into account real-time market dynamics, competitive landscapes, consumer profiles, and other key pricing factors.[6,7,8]

The telecommunications, retail, transportation, banking, and education sectors demonstrate the highest levels of AI adoption, as reported in research conducted by McKinsey & Company. AI-driven automation technologies play a pivotal role in the digital transformation endeavors of nations, contributing significantly to the development of digital economies.[9] Recent years have witnessed the digitalization of economies through innovations in Information and Communication Technologies (ICTs), substantially influencing the economic landscape of countries.[10] Within the ASEAN region, reports

man.2007.07.016.

3 Anup Aprem and Stephen J. Roberts, "Optimal Pricing in Black Box Producer-Consumer Stackelberg Games Using Revealed Preference Feedback," *Neurocomputing* 437 (May 2021): 31–41, https://doi.org/10.1016/j.neucom.2021.01.026; Salma Taik and Bálint Kiss, "Selective and Optimal Dynamic Pricing Strategy for Residential Electricity Consumers Based on Genetic Algorithms," *Heliyon* 8, no. 11 (2022): e11696, https://doi.org/https://doi.org/10.1016/j.heliyon.2022.e11696.

4 Wenjia Han and Billy Bai, "Pricing Research in Hospitality and Tourism and Marketing Literature: A Systematic Review and Research Agenda," *International Journal of Contemporary Hospitality Management* 34, no. 5 (April 4, 2022): 1717–38, https://doi.org/10.1108/IJCHM-08-2021-0963; Isabel P. Riquelme, Sergio Román, and Pedro J. Cuestas, "Does It Matter Who Gets a Better Price? Antecedents and Consequences of Online Price Unfairness for Advantaged and Disadvantaged Consumers," *Tourism Management Perspectives* 40 (October 2021): 100902, https://doi.org/10.1016/j.tmp.2021.100902.

5 Choi, Song, and Jing, "Let Your Algorithm Shine: The Impact of Algorithmic Cues on Consumer Perceptions of Price Discrimination."

6 Calvano et al. (2019)

7 Kyle Manley, Charity Nyelele, and Benis N. Egoh, "A Review of Machine Learning and Big Data Applications in Addressing Ecosystem Service Research Gaps," *Ecosystem Services* 57 (October 1, 2022): 101478, https://doi.org/10.1016/J.ECOSER.2022.101478.

8 Juan-Pedro Cabrera-Sánchez and Ángel F. Villarejo-Ramos, "Acceptance and Use of Big Data Techniques in Services Companies," *Journal of Retailing and Consumer Services* 52 (January 2020): 101888, https://doi.org/10.1016/j.jretconser.2019.101888.

9 McKindsey and Company, "The Economic Potential of Generative AI:The Next Productivity Frontier," 2023, https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/the-economic-potential-of-generative-ai-the-next-productivity-frontier#introduction.

10 Sofia Gomes and João M. Lopes, "ICT Access and Entrepreneurship in the Open Innovation Dynamic Context: Evidence from OECD Countries," *Journal of Open Innovation: Technology, Market, and Complexity* 8, no. 2

from Google, Temasek, and Bain & Co reveal that Indonesia stands as the leading player in the digital economy, contributing 41.9% of the total digital economic transactions within ASEAN (Figure 1). Projections indicate that the value of Indonesia's digital economy within the Indonesian e-commerce sphere is set to nearly double, surging from $53 billion in 2021 to an anticipated $104 billion by 2025.[11] This growth is significantly attributed to a multitude of businesses capitalizing on digital economic opportunities facilitated by information technology, particularly through the utilization of big data and Artificial Intelligence.[12]

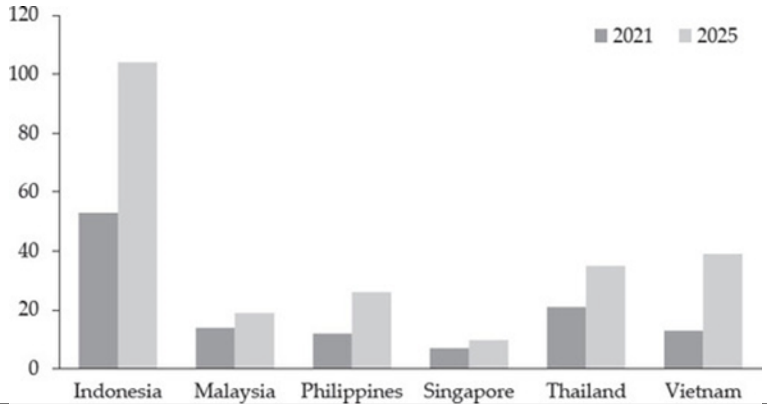

Figure 1. Size of E-Commerce in Southeast Asia, 2021 and 2025 ($ billion)

Source: Google, Temasek and Bain & Co.[13]

The US, EU, and China have been at the center of digital economy competition law concerns in recent years. Digital technology's constant innovation drives this concentration. The use of pricing algorithms, particularly deep learning algorithms in artificial intelligence, is an increasing trend in digital commerce, especially in competitive dynamics. The paper also notes that algorithmic pricing in digital services can reduce consumer surplus and encourage corporate collusion to set prices in oligopolistic markets with rivals. The complex interaction of algorithms in cyberspace, which can react, makes detection difficult for competition authorities. Algorithmic pricing research often finds latent coordination among autonomous pricing algorithms, resulting in pricing outcomes that resemble collaboration despite the algorithms' independent pricing. Competition authorities struggle to reach appropriate findings due to this issue.[14,15,16]

(June 15, 2022): 102, https://doi.org/10.3390/joitmc8020102.entrepreneurship has become increasingly important for innovation and economic growth. However, few studies demonstrate the role of information and communication technology systems (ICT

11 (Coordinating Ministry for Economic Affairs of the Republic of Indonesia, 2021)

12 Kompas, "Pentingnya Teknologi Kecerdasan Buatan Bagi Pelaku Bisnis," Advertorial Kompas, 2017, https://biz.kompas.com/read/2017/09/15/093338228/pentingnya-teknologi-kecerdasan-buatan-bagi-pelaku-bisnis.

13 Temasek and Bain & Company Google, "E-Conomy SEA 2021," 2021, https://www.temasek.com.sg/content/dam/temasek-corporate/news-and-views/resources/reports/e-conomy-sea-2021-report.pdf.

14 Cassey Lee, "Competition Policy in the Age of Algorithms: Challenges for Indonesia," *Bulletin of Indonesian Economic Studies* 58, no. 3 (September 2, 2022): 297–312, https://doi.org/10.1080/00074918.2022.2125488; Wolfgang Kerber, "Updating Competition Policy for the Digital Economy? An Analysis of Recent Reports in Germany, UK, EU, and Australia," *SSRN Electronic Journal*, 2019, https://doi.org/10.2139/ssrn.3469624.

15 Ilgin Isgenc, "Competition Law in the AI ERA: Algorithmic Collusion under EU Competition," *Trinity College Law Review* 24 (2021), https://heinonline.org/HOL/Page?handle=hein.journals/trinclr24&id=43&div=&collection=.

16 Hans-Theo Normann and Martin Sternberg, "Human-Algorithm Interaction: Algorithmic Pricing in Hybrid Laboratory Markets," *European Economic Review* 152 (February 2023): 104347, https://doi.org/10.1016/j.euro-

This research conducts a comprehensive literature review, addressing two key research inquiries pertaining to algorithm pricing within the context of Indonesian Competition Law. To formulate our research questions, we adhered to the PICO framework as outlined by,[17] aligning them with the objectives of this overview. The ensuing research queries are as follows: the first (RQ1) seeks to ascertain the characteristics of algorithms and the prevailing trends underpinning adaptive pricing strategies. The second query (RQ2) delves into the assessment of the sufficiency of Indonesian competition law in effectively addressing the latest feature developments and emerging trends within pricing algorithms.

2. ANALYSIS AND DISCUSSION

2.1. Methods

This study searched all adaptive pricing algorithmic models, schemes, and methodology papers. Keywords have been used to help retrieve relevant literature from the database. 'Adaptive pricing,' 'Dynamic pricing,' 'Algorithm,' 'Model,' 'Method,' and 'Scheme.' They were systematically integrated using Boolean operators like 'AND' and 'OR' to refine search results, focusing on algorithmic trends in adaptive pricing, particularly in markets and e-commerce. The analysis only covers English-language peer-reviewed journal articles during 2018–2022. Conference proceedings, brief communications, magazines, and novels are excluded from this review. The search queries are implemented in ScienceDirect and Scopus using language, period, keyword, and article type criteria. A thorough and tailored search is achieved by applying these queries to titles, abstracts, and keywords. The literature exploration search phrases are shown below.:

2.1.1 SCOPUS: (TITLE-ABS-KEY ("adaptive pricing") OR TITLE-ABS-KEY ("dynamic pricing") AND TITLE-ABS-KEY (algorithm) AND TITLE-ABS-KEY (scheme) OR TITLE-ABS-KEY (model) OR TITLE-ABS-KEY (method) AND TITLE-ABS-KEY (market) OR TITLE-ABS-KEY (commerce)) AND PUBYEAR > 2017 AND PUBYEAR < 2023 AND PUBYEAR > 2017 AND PUBYEAR < 2023

2.1.2 ScienceDirect: ("adaptive pricing" OR "dynamic pricing") AND algorithm AND (scheme OR model OR method) AND (market OR commerce)

2.1.3 Data selection

Table 1. Criteria for inclusion and exclusion in study selection

	Criteria
Inclusion	Published works from 2018 to 2022 Peer-reviewed journal article Full-text article Empirical and conceptual articles on adaptive pricing algorithm.

ecorev.2022.104347.

17 Pollock & Berge (2018)

Exclusion	Articles are written in another language besides English Articles from proceedings, conference papers and reviews, magazines, books, and book chapters The article does not discuss specific adaptive pricing algorithms or their applications

As an integral part of the study's selection process, specific inclusion and exclusion criteria were established to ensure the consideration of only those articles that directly align with the research query. The study encompasses articles that delve into algorithmic models applied in dynamic pricing across diverse market sectors, such as dynamic air ticket pricing or dynamic pricing within electrical power markets. Table 1 exhaustively lists article filtration inclusion and exclusion criteria. The initial search query returned 177 publications from two major databases from 2018 to 2022: 140 from Scopus and 37 from Science Direct. After applying exclusion criteria, this initial pool of articles dropped from 177 to 122. Mendeley Reference Manager merged all search results articles into its bibliographic database. The screening process followed the PRISMA flowchart (Fig. 1). These items undergo a thorough, three-step screening. The first step of filtering eliminated duplications, anonymous research, and studies that were not original peer-reviewed journal publications, leaving 100 articles. The second level organized and reviewed titles and abstracts to categorize dynamic pricing algorithm studies across markets and e-commerce areas. The entire texts of 100 publications relevant to the study's aims were examined and assessed during this phase. The third screening phase involved a thorough assessment of full-text publications to determine their compliance with Table 1 criteria. This comprehensive examination yielded 69 articles that satisfied the criteria. The study's methodology included iterative examination and validation of these articles' dat

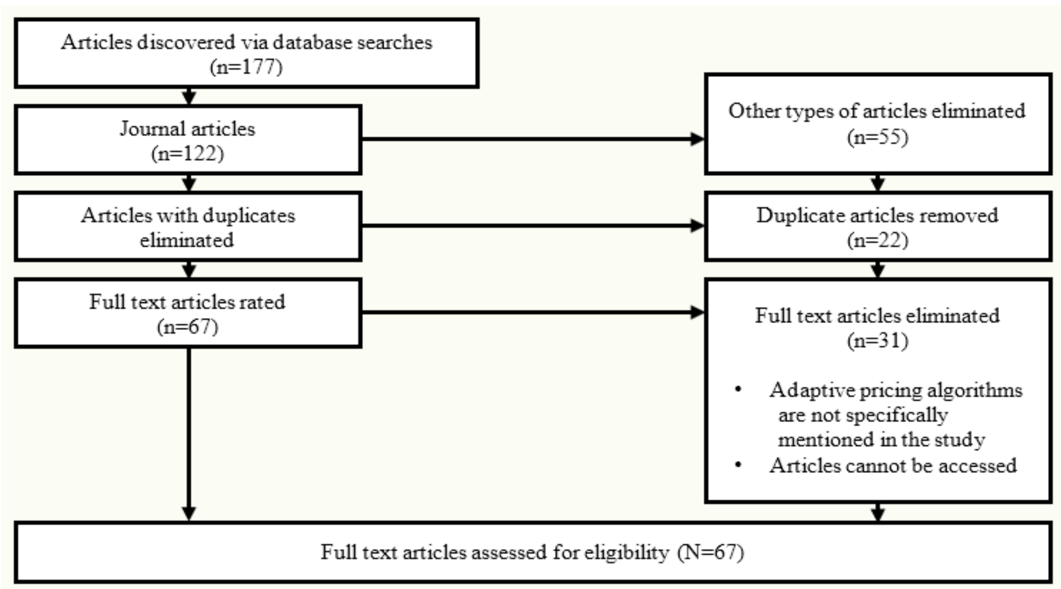

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Figure 2. The screening procedure of articles is based on the PRISMA flowchart.

2.1. The Features and The Current Trends of Algorithms Used in Adaptive Pricing

Several types of adaptive pricing methods are used in the process of electricity and alternative energy management (table 2), retail management (table 3), transportation management (table 4), and the multimedia service management and other sectors in several studies (table 5)

Table 2. Summary of adaptive pricing algorithms used in the energy management sector in several studies

Methodologies	Types	References
A game theory-based Demand Response Program model (GTDRP) with an enthusiasm-assisted teaching-and-learning-based optimization algorithm (ETLBO)	GT	21
Stackelberg's game with a Lagrange multiplier	GT	22
Game theory based on the non-cooperative Stackelberg model with a non-sorting genetic algorithm II (NSGA-II) algorithm	GT	23
Stackelberg's hierarchical gaming approach with the Lagrange function	GT	24
The Stackelberg game model is solved by a multiple mutation differential evolution algorithm.	GT	25
Long short-term memory (LSTM)	RL	26
Long short-term memory (LSTM) networks and the Q-learning method	RL	27
Deep Q learning (DQL) and deep recurrent neural network (RNN) integrated model	RL	28
Peer-to-peer (P2P) energy trading framework with Q learning	RL	29
Deep reinforcement learning (DRL)	RL	30
Artificial neural networks (ANN)	RL	31
Convolutional neural networks (CNN)	RL	32
Deep deterministic policy gradient (DDPG) reinforcement learning algorithm	RL	33
Reinforcement learning (RL) model created using adaptive filtering algorithms, adaptive heuristic criticism (AHC-Fast), and recursive least squares (RLS)	RL	34
a Q-learning algorithm and alternating direction multiplier (ADMM) method algorithm	RL	35
Monte Carlo Tree Search (MCTS) algorithm	RL	36
generic heuristic algorithms GREEDY and SLIDING-WINDOW	HR	37
Genetic algorithm (GA)	HR	38
Genetic Algorithm (GA)	HR	39
Crossover method of Genetic Algorithm (GA)	HR	40
A customized hierarchical genetic algorithm (GA)	HR	41
genetic algorithm (GA)	HR	42

Asynchronous advantage actor-critic (A3C) algorithms and neural networks	HR	43
New least squares version of the multi-input and multi-output (MIMO)-based support vector machine (SVM) model and enhanced particle swarm optimization algorithm (PSO)	HR	44
A particle swarm optimization algorithm-based super twisting sliding mode controller (PSO-STSMC)	HR	45
A hybrid analytic hierarchical process (AHP) and a power deep learning algorithm (DL), the particle swarm optimization algorithm (PSO)-based price optimization	HR	46
Cuckoo search (CS), adaptive cuckoo search (ACS), and Hybrid genetic algorithm (GA)- particle swarm optimization algorithm (PSO)	HR	47
A heuristic-based cost optimization algorithm	HR	48
Metaheuristic algorithm and Taguchi orthogonal array testing (TOAT) method	HR	49
Dijkstra's algorithm	OT	50
A distributed gradient projection iterative algorithm	OT	51
A master-slave game equilibrium algorithm based on the Kriging meta-model	OT	52
Bayesian-Nash equilibrium solving algorithm	OT	53
A two-level distributed algorithm	OT	54
A two-tier hybrid demand modeling framework consists of a stacked auto-encoder (SAE), a deep learning (DL) technique appropriate for real-valued input, and an adaptive neuro-fuzzy inference system (ANFIS)	OT	55
A hybrid demand modeling framework using optimal energy management algorithms	OT	56
a deep contextual bandit algorithm	MB	57

Table 3. Summary of adaptive pricing algorithms used in the retail management sector in several studies

Methodologies	Types	References
Two ground truth algorithms (value iteration and real request response policy) and two classical Reinforcement Learning (RL) algorithms (double Q learning and Q learning) were compared to the TN-DDQN algorithm	RL	38
the efficacy of Deep Q-Networks (DQN) and Soft Actor-Critic (SAC)		39
a price Q-learning mechanism	RL	40
a Q-learning algorithm model based on a neural network	RL	41
Microeconomic choice theory is proposed as an extension of the multi-armed bandit (MAB) algorithm from statistical machine learning.	MB	42
One is based on the novel "balanced exploration" paradigm, and the other is a dual-primal algorithm with multiplicative updating.	MB	43

(1) SHALLOWPRICING, which is based on a shallow ellipsoid cut and permits the addition of a margin of safety for each slice, and (2) ELLIPSOIDEXP4, which combines the SHALLOW-PRICING algorithm with EXP4 standard adversarial contextual bandits.	MB	44
A meta-heuristic (GA) genetic algorithm	HR	45
A two-stage heuristic algorithm	HR	46
heuristic algorithms and League Championship algorithms	HR	47
Two distinct metaheuristic algorithms, the first combines Optic Inspired Optimization (OIO) with MCNFP, while the second combines Improved Particle Swarm Optimization (IPSO) with MCNFP	HR	48
A standard genetic algorithm (GA), a two-level evolutionary algorithm,	HR	49
a new algorithm based on Bayesian inference, bootstrap-based confidence estimation, and kernel regression	OT	50
Regularized Maximum Likelihood Pricing (RMLP)	OT	51
a random search algorithm and an experimental design (to discover nearly optimal backfill and dynamic pricing policies for a static environment)	OT	52
Dynamic pricing for the Long Tail (DynaLT)	OT	53

Table 4. Summary of adaptive pricing algorithms used in the transportation management sector in several studies

Methodologies	Types	References
reinforcement learning-enhanced agent-based modeling and simulation system (RL-ABMS)	RL	54
Markov Decision Process, and Reinforcement Learning (RL), specifically a state-action-reward-state-action (SARSA) algorithm	RL	55
dynamic pricing algorithm based on reinforcement learning (RL), Q-learning	RL	56
Reinforcement Learning (RL) is combined with Genetic Algorithm (GA) in order to create hybrid algorithms	HR	57
a stochastic nonlinear mathematical model, a particle swarm algorithm	HR	58
a two-stage analytical algorithm	OT	59
The Planning, Pricing, and Backlog Controlling (PPBC) algorithm, which is based on the Lyapunov drift-plus-penalty method, the harmony search algorithm	OT	60
Lyft Application Programming Interface, The Facebook Prophet model, the Random Forest model	OT	61
Oblique convergence algorithm	OT	62

Table 5. Summary of adaptive pricing algorithms used in multimedia service management and other sectors in several studies

Methodologies	Types	References
Dynamic Pricing with Traffic Engineering (DPTE), heuristic algorithm	HR	63

mobile network operators (MNOs), access points (APs), and market-derived consumers using a three-stage Stackelberg game	GT	64
The augmented Lagrange multiplier method, a dynamic closed-loop control scheme	OT	65
a-path of the uncertain differential equation, numerical algorithms	OT	66
Pareto optimization, A multi-objective solution method, a multi-objective evolutionary algorithm (MOEA)	OT	67

Table 6. Distribution of algorithm types used in previous research articles (2018-2022)

Algorithm type	**Number of Studies**					**Total**	**Percentage (%)**
	Energy management	**Retail management**	**Transportation management**	**Multimedia service management**	**Others**		
Reinforcement learning	11	7	4			22	32.84
Heuristics	11	4	1	1		19	28.35
Multiarmed Bandits	1	3				4	5.97
Game theory models	5			1		6	8.96
Others	7	4	4		3	18	26.86
Total	35	18	9	2	3	67	100

According to the data distribution presented in Table 6, it becomes evident that the prevailing choice of algorithm type within the previous study is primarily centred around two categories: reinforcement learning and heuristic algorithms, accounting for substantial percentages of 32.84% and 28.35%, respectively.

Reinforcement learning (RL) is a machine-learning algorithm that solves complex problems by trial and error, similar to human learning. Exposing the RL system to real-world scenarios trains it to make decisions. Positive environmental rewards increase an agent's likelihood of repeating comparable activities, while negative rewards decrease them. Reinforcement learning methods in dynamic pricing research help producers maximize revenues by prioritizing long-term gains over transactional rewards.[18] Business

18 C Yin and J Han, "Dynamic Pricing Model of E-Commerce Platforms Based on Deep Reinforcement Learning," *CMES - Computer Modeling in Engineering and Sciences* 127, no. 1 (2021): 291–307, https://doi.org/10.32604/cmes.2021.014347.its application field has gradually expanded. To further apply the deep reinforcement learning technology to the field of dynamic pricing, we build an intelligent dynamic pricing system, introduce the reinforcement learning technology related to dynamic pricing, and introduce existing research on the number of suppliers (single supplier and multiple suppliers

actors and competitors may have illegal agreements, which competition law enforcement should consider. An agreement or mutual understanding amongst the artificial agents of collaborating organizations is vital currently. The focus is shifting from collusion to price algorithms that mutually govern and regulate market prices.

2.2. The Adequacy of the Legal Instrument and Approach to Deal with The Current Feature Developments in The Pricing Algorithm

Due to the shift from the traditional to the digital economy, the Business Competition Supervisory Commission faces a major legal issue regarding the distinction between autonomous parallel actions and RL-enabled "concerted actions." A 2015 US Department of Justice case accused David Topkins of manipulating prices with other online poster suppliers. This case revealed a "deal," in which Topkins and his colleagues constructed and distributed a dynamic price "algorithm" to carry out their agreement. When market participants independently construct algorithms with decision parameters that react to others' decisions to sustain or reinforce coordinated results, more complex circumstances arise.[19] To begin, it is worth noting that as early as 1992, the Federal District Court acknowledged that an algorithm could transcend being a mere "tool" when it was assigned the responsibility of assessing various factors to directly determine a motorboat safety rating.[20]

2.3.1 Taxonomy of Algorithmic Contracts

Algorithmic contracts use algorithms to set terms and conditions. Indeed, algorithmic contracts include clauses and provisions established by algorithms rather than humans. Algorithms are systematic processes or procedures used to calculate or solve computer issues.[21] The main difference between algorithms and human decision-makers is that algorithm-driven computers are simpler and faster. RL, trained on multiple patterns and data, allows algorithms to examine many elements across scenarios, surpassing human capability. Many activities use algorithms, making it difficult for their developers to predict their behavior.[22]

Understand algorithmic contracts' complexity by studying contract-generating algorithms. There are numerous ways to build contracts using algorithms. If their decision-making is predictable and complicated, algorithms can be used as tools or artificial agents. Artificial agent transparency can be further divided into a clear box and a black box. Clear-box algorithms are human-friendly, while black-box algorithms are not.[23] Similar to how parties use calculators or spreadsheets to make offers or acceptances, contracts in which algorithms are tools do not raise new contract law difficulties. When contract algorithm agents act as artificial agents "negotiating or coordinating," contract law should treat them more explicitly.[24]

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19 Ariel Ezrachi and Maurice E. Stucke, "Artificial Intelligence & Collusion: When Computers Inhibit Competition," *University of Illinois Law Review* 2017 (2017), https://heinonline.org/HOL/Page?handle=hein.journals/unilllr2017&id=1816&div=&collection=.

20 Lauren Henry Scholz, "Algorithmic Contract," *Standford Technology Law Review* 128 (2017): 134.

21 Yuri Gurevich, "What Is an Algorithm? (Revised)," in *Logic, Mind, and Nature*, 2014, http://research.microsoft.com/en-us/um/people/gurevich/Opera/209a.pdf.

22 Ryan Calo, "Robotics and the Lessons of Cyberlaw," *California Law Review* 103 (2015).

23 Scholz, "Algorithmic Contract."

24 Scholz.

2.3.2 Dynamic Pricing and Black Box Algorithmic Contract Status

Dynamic pricing involves considering market, product, and buyer information to establish a price that aligns with the maximum amount a buyer is willing to pay.[25] It serves as an illustrative instance of how algorithmic contracts can serve as gap-fillers. Sellers employ algorithms to factor in market data and personalized insights about potential buyers, enabling them to determine the most appropriate pricing. In the majority of retail scenarios, be it in business-to-business or business-to-consumer transactions, pricing tends to be presented as a "take it or leave it" proposition.[26]One of two legal notions needs to be added to contract law to make Black Box Algorithmic Contracts more enforceable. First, black box algorithmic contracts may be tools. Another way is to recognize that smart organizations can understand Black Box Algorithmic Contracts from an agency-based perspective. Instead of ignoring Black Box Algorithmic Contracts' essential characteristics, the latter approach would better reflect their operational dynamics. This method could naturally reduce the risk of irresponsible and intentional algorithm usage in contract negotiation and formation.

Some argue that general contract law cannot universally justify the binary classification of sophistication—those who are sophisticated in contract matters and those who are not—because it creates separate contract regulations for companies and individuals. Black box algorithmic contracts test this argument. Private law has failed to adapt to artificial intelligence, even if black box algorithms can function beyond the comprehension and intentions of their authors. Algorithmic contracts are unenforceable due to compelling arguments. A contract is usually a compromise between two or more parties to change their legal rights. Competent parties, free from compulsion, can choose the terms they want to be legally bound by, regardless of sophistication. A contract requires informed and objective assent to the terms. Unlike traditional contracts, black-box algorithmic contracts provide distinct challenges. The algorithm's actions may be unknown to both parties. Usually, pursuing a profitable goal does not form a contract. While algorithms make precise decisions, their regulation differs from that of conscious human decisions, akin to autonomous weaponry.[27,28] Much like agents, algorithms should not be perceived as mere extensions of the will of individuals or companies. Legal expert in robotics, Ryan Calo, characterizes emergence as "unpredictable behaviour",[29] referring to behavior that seemingly achieves a goal in a manner that the algorithm's creator cannot anticipate, arising from learning and self-modification based on prior behavior. If the instructions provided to the algorithmic agent by the principal are unclear, these instructions may not constitute an objectively manifested intent upon which a contractual promise can be founded.

25 Robert M. Weiss & Ajay K. Mehrotra, "Online Dynamic Pricing: Efficiency, Equity and the Future of E-Commerce," *Virginia Journal of Law and Technology* 11, no. 1 (2001).

26 Wendy Netter Epstein, "'Facilitating Incomplete Contracts' by Wendy Netter Epstein," *Case Western Reserve Law Review* 65, no. 2 (2014): 297–300, https://scholarlycommons.law.case.edu/caselrev/vol65/iss2/4/; Scholz, "Algorithmic Contract."

27 (M.R. Miller, 2010)

28 F. Patrick Hubbard, "'Sophisticated Robots': Balancing Liability, Regulation, and Innovation," *Florida Law Review* 66, no. 5 (2014), https://scholarcommons.sc.edu/cgi/viewcontent.cgi?article=2027&context=law_facpub.

29 Calo, "Robotics and the Lessons of Cyberlaw."

The offeror's agents automatically create offers that the they may or may not consider. The key question is whether a party's claimed intention to use an algorithm to choose prices and contract terms matches the algorithm's actual contract terms. This is not always true. Algorithms act as agents between their creators' goals. The algorithm can express the offeror's objective goal when it functions within what the it clearly desires to do. This is an illusory promise that the it will sign a black-box algorithmic contract. An illusory promise without duties is not a contract. Contracting parties should not be able to circumvent contract law with new technologies. The assumption that those using algorithms have some insight into their activities underlies some of society's limited awareness of algorithms. An agent may act in a way that conflicts with the principal's goals and interests under agency law. Since the principal incurred risks when hiring the agent, the principal is usually liable for agent errors.[30]

Algorithms, operating in a manner akin to human agents, invoke the applicability of agency law, albeit qualified as "constructive" due to algorithms lacking human attributes. Agency law permits the legal system to consider the intentions of principals who are not directly engaged in the contractual formation process. Principals can formally authorize their agents, implying that they derive benefits from the actions undertaken by these agents. This approach aligns well with contemporary contract law but extends the law's formal boundaries somewhat. The Uniform Electronic Transactions Act (UETA) encompasses the concept of algorithms as agents.[31] UETA facilitates the establishment of algorithmic contracts by recognizing such contracts as formed through algorithms referred to as "electronic agents." Consequently, electronic records and signatures facilitated by electronic agents hold the same legal standing as manual records and signatures, as stipulated by.[32] An "electronic agent" is defined as a computer program or automated means employed independently to initiate or respond to electronic actions in whole or in part, without requiring human intervention.[33] Furthermore, Section 14 of UETA pertaining to Automated Transactions states that "A contract may be formed by the interaction of electronic agents of the parties, even if no individual reviewed the electronic agent's actions." The subsequent question to address pertains to the liability incurred if an "electronic agent" undertakes an action that deviates from the principal's intentions.

There are three distinct perspectives regarding the legal status of electronic agents. The first viewpoint, referred to as the 'traditional approach,' perceives electronic agents solely as tools employed by users. The second perspective, termed the "modern approach," conceptualizes electronic agents as legal entities or persons. Nevertheless, no legal system has hitherto recognized electronic agents as distinct legal entities separate from their users. The third perspective, denoted as the "progressive approach," challenges the notion of an independent 'electronic person.' Instead, it suggests that electronic

30 Melvin Aron Eisenberg, "Donative Promises," *The University of Chicagho Law Review* 47, no. 1 (1979), https://chicagounbound.uchicago.edu/cgi/viewcontent.cgi?article=4186&context=uclrev; Robert A. Prentice, "Law & Gratuitous Promises," *SSRN Electronic Journal*, 2006, https://doi.org/10.2139/ssrn.908929.

31 Section 2 [6] and Section 14 [1] and [2] of the Uniform Electronic Transactions Act, 1999

32 Patricia Brumfield Fry (2000)

33 (Sec. 2[6] of the Uniform Electronic Transactions Act, 1999)

agents might be better characterized as “registered agents”.[34] Under this approach, an agent’s owner can provide it with a designated sum of money by enlisting it in a registry, resulting in the creation of an agent with limited liability.

2.3. Readiness of Indonesian Competition Law to Respond to Contracts between Electronic Agents

The Business Competition Supervisory Commission’s KPPU Regulation Number 4 of 2011 defines “price fixing.” Price determination based on a documented agreement is what this regulation means. Importantly, a company’s price does not violate Article 5 of Law Number 5 of 1999 without an agreement with other enterprises. Article 1, number 7, of Law Number 5 of 1999 defines an “agreement” as “an act in which one or more business actors mutually obligate themselves to engage in business activities under any designation, whether it is in written or unwritten form.” The practice of “price fixing agreements” in Law Number 5 of 1999 is oligopolistic market pricing collusion.

Reviewing from George J. Stigler’s oligopoly theory outlined in 1964, it is established that the coordination among business entities leading to anti-competitive conduct necessitates the fulfillment of at least three cumulative conditions.[35] In a more recent context, Michal S. Gal, in his 2018 work titled “Algorithms as Illegal Agreements,” responded to Stigler’s assertions by highlighting the role of algorithms in facilitating coordination. This facilitation is achieved through mechanisms such as data utilization, storage, connectivity, and comprehensive analysis, ultimately enhancing the feasibility of satisfying Stigler’s coordination requirements.[36]

In light of “electronic agents” (EAs)’ ability to coordinate agreement transactions, Article 5 of Law Number 5 of 1999 and *KPPU* Regulation Number 4 of 2011 should be rewritten to reflect current developments, particularly regarding price-fixing classification. Legal advances like Law Number 19 of 2016, which revised Law Number 11 of 2008, the Information and Electronic Transactions Law, are instructive. An “Electronic Contract” (EC) is an agreement between parties made by an electronic system, according to ITE Law. ITE Law ECs can be created through EA interactions. Article 1, point 8 of the ITE Law defines an “electronic agent” as a device in an electronic system that automates particular operations on electronic information under human control. ITE Law also holds the registered electronic agent operator liable for the legal consequences of electronic transactions, especially when EAs make mistakes.

The definition of Electronic Agents (EAs) within the ITE Law is rather straightforward, lacking specific provisions regarding whether one EA can engage in coordinated interactions with other EAs. Notably, as highlighted by Hubbard and

34 Sachin Mishra, “The Legal Status of Electronic Agents,” 2022, https://www.legalserviceindia.com/article/l245-Electronic-agents.html.

35 George J Stigler, “A Theory of Oligopoly,” *Journal of Olitical Economy* 72, no. 1 (1964), https://www.journals.uchicago.edu/doi/abs/10.1086/258853. See: These conditions encompass: 1) The attainment of a mutual understanding or agreement regarding trade terms; 2) The capacity to detect deviations from a supra-competitive equilibrium; and 3) The establishment of a credible threat of retaliation to deter any potential deviations.

36 Michal S Gal, “Algorithms as Illegal Agreements on JSTOR,” Berkeley Technology Law Journal 34, no. 1 (2019): 99, https://www.jstor.org/stable/26755226.

Epstein, algorithmic contracts can arise from the interactions of two electronic agents.[37] Furthermore, Stigler's stipulation regarding one of the prerequisites for an oligopoly, which is the establishment of understanding,[38] underscores how "algorithms" play a role in facilitating "coordination" among business actors.[39] EAs are often viewed as "gap-filling negotiators".[40] In contrast, the definition of EAs within the Uniform Electronic Transactions Act (UETA) is notably more progressive, characterizing EAs as "a computer program or an electronic or other automated means used independently to initiate an action or response to electronic records or performances in whole or in part, without review or action by an individual".[41] This definition suggests that EAs have the capacity to act autonomously without the need for human oversight.

Electronic agents (EAs) can be broadly categorized into two main types, as outlined by: a) Reactive agents (RA) and b) Multi-Agent systems (MAs).[42] Considering these types of electronic agents, it becomes apparent that the definition of EAs within the ITE Law aligns more with reactive agents. As defined in Article 1 point 8 of the ITE Law, EAs are described as entities that "...carry out an action on certain electronic information automatically which is held by a person." EAs, according to the ITE Law, operate when they receive instructions from their environment, which primarily consists of "individuals or people." In the context of price cartels, governed by Article 5 of Law Number 5 of 1999, such collaborations tend to occur in oligopoly markets where business actors engage in "coordination" with each other.[43] This coordination can be facilitated by algorithms.[44]

Based on this analysis, it can be inferred that the concept of a "price fixing " as outlined in Indonesian Competition Law and *KPPU* Regulation Number 4 of 2011 KPPU should undergo an expansion in scope. Firstly, it should encompass the notion that the "coordination" among business actors involved in price cartels can be facilitated by electronic agents (EAs). Secondly, with respect to EAs, Article 1 point 8 of the ITE Law requires reformulation. It should not be limited to EAs merely acting as tools that function in response to individual orders.[45] Instead, it should acknowledge their capacity to function as Artificial Intelligence Agents capable of autonomous action "without any orders from individuals".[46] By reformulating the norm related to "price fixing agreements," it is anticipated that the KPPU will be better equipped to detect instances of anti-competitive behaviour facilitated by electronic agents and to establish accountability in such cases.

3. CONCLUSION

37 Hubbard, "'Sophisticated Robots': Balancing Liability, Regulation, and Innovation"; Epstein, "'Facilitating Incomplete Contracts' by Wendy Netter Epstein."

38 Stigler, "A Theory of Oligopoly."

39 Gal, "Algorithms as Illegal Agreements on JSTOR."

40 Scholz, "Algorithmic Contract."

41 **(Sec. 2(6) of the Uniform Electronic Transactions Act, 1999)**

42 Geeks, (2021) and Harré (2021). See: RA is EAs respond to direct stimuli from their environment and take actions based on these stimuli. MAs is These agents may need to coordinate their actions and communicate with one another to attain their goals

43 (Stigler, 1964)

44 Gal, "Algorithms as Illegal Agreements on JSTOR."

45 Scholz, "Algorithmic Contract."

46 **(Section 2(6) of the Uniform Electronic Transactions Act, 1999)**

The literature review of adaptive pricing algorithms published between 2018 and 2022 shows that RL, a machine-learning algorithm that imitates human learning, is the most widely used. Competition law enforcement should investigate illegal agreements between collaborating corporations' artificial agents. Understanding the taxonomy of algorithmic agreements and price determination is necessary to resolve this legal issue. When algorithmic agents act as artificial agents "negotiating or coordinating," competition law should approach them more explicitly. Due to EAs' ability to coordinate agreement transactions, Article 5 of Law Number 5 of 1999 and Regulation of the Business Competition Supervisory Commission Number 4 of 2011, particularly regarding price-fixing agreement classification, must be revised to reflect current developments, such as "EAs" as exemplified by Law Number 19 of 2016 on ITE Law. Indonesian Competition Law should broaden the "price fixing agreement" definition. EAs should facilitate "coordination" among pricing cartel business parties. Second, the ITE Law needs EA revision. It should go beyond EAs being tools that follow directions. Instead, it should recognize their ability to behave autonomously "without any orders from individuals" as AI agents.

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