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Competition in Algorithmically Mediated Markets: Strategic Implications of Automated Pricing, Recommendation Systems, and Data-Driven Interactions

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Abstract

Competition in algorithmically mediated markets is undergoing a profound transformation driven by automated pricing, recommendation systems, and data-driven interactions. This managerial and strategic perspective article synthesizes contemporary research to elucidate how these algorithmic tools reshape firm rivalry, consumer engagement, and market structures. Automated pricing algorithms enable real-time, personalized price adjustments that accelerate competitive responses but also raise the specter of tacit collusion among independent systems. Recommendation systems, in turn, act as powerful market-shaping mechanisms by controlling product visibility and influencing demand formation in platform environments. Data-driven interactions further personalize consumer experiences, fragment markets, and require firms to compete based on data intelligence and algorithmic alignment. Platforms serve as critical intermediaries, structuring the rules of engagement and mediating the flows of information and value. The article identifies key strategic challenges, including opacity in decision-making, loss of managerial control, and risks of unintended coordination. To address these, a strategic competition framework is introduced, comprising five components: automated pricing capability, recommendation and visibility management, data acquisition and interaction intelligence, strategic monitoring and human oversight, and adaptive competitive response loops, which maps the architecture of data flows, algorithmic processing, market outcomes, and managerial intervention points. The analysis offers practical guidance for managers on developing capabilities to compete effectively in automated environments, emphasizing the need to balance automation with strategic human oversight and governance mechanisms. By integrating insights from strategic management and digital business literature, this article equips executives with the conceptual tools to navigate and capitalize on the opportunities and risks of algorithmically mediated competition.

Keywords Algorithmic pricing, Recommendation systems, Platform-mediated competition, Data-driven interactions, Strategic rivalry, Algorithmic collusion

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Introduction

The competitive landscape has shifted decisively toward algorithmically mediated markets, where automated systems now govern pricing, product visibility, and consumer interactions at unprecedented speed and scale.

Traditional strategic models predicated on observable price signals, direct product differentiation, and human-led negotiations are increasingly supplanted by algorithmic processes that operate continuously and invisibly to human observers [1-3]. Firms no longer compete solely against rivals; they compete within ecosystems defined by pricing

algorithms, recommendation engines, and data-driven platforms that actively construct demand and allocate attention [4-6]. This mediation introduces novel strategic imperatives: managers must design, monitor, and respond to systems that learn autonomously, personalize at the individual level, and generate feedback loops that amplify or dampen competitive intensity [7-9].

The implications extend beyond operational efficiency. Automated pricing enables dynamic, context-aware adjustments that can optimize revenue while simultaneously fostering emergent coordination among rivals, even in the absence of explicit agreements [1, 10, 11]. Recommendation systems, deployed across e-commerce and content platforms, function as gatekeepers of market visibility, determining which offerings reach consumers and thereby reshaping the competitive playing field from product-centric rivalry to algorithm-centric positioning [12-14]. Data-driven interactions further complicate strategy by enabling hyper-personalized engagements that fragment consumer segments and erode the value of aggregate market analysis [15-17]. Platforms, acting as digital intermediaries, impose their own algorithmic architectures, constraining firm autonomy while providing the infrastructure through which competition unfolds [18-20].

From a managerial perspective, these developments demand a reevaluation of core strategic capabilities. Executives can no longer rely on periodic pricing reviews or static market research; instead, they must cultivate continuous oversight of algorithmic outputs, anticipate rival algorithm behaviors, and intervene when automated processes deviate from intended strategic goals [7, 21, 22]. The opacity inherent in many machine-learning models exacerbates this challenge, rendering causal attribution of market outcomes difficult and complicating both internal governance and external regulatory compliance [8, 23, 24]. Moreover, the velocity of algorithmic decision-making compresses strategic response windows, requiring organizations to develop hybrid human-AI decision architectures that preserve managerial judgment amid automation [11, 25].

Table 1 contrasts the underlying logic of traditional market competition with the structural dynamics of algorithmically mediated competition, clarifying why rivalry now depends on visibility control, data intelligence, and hybrid governance rather than on product and price competition alone.

Table 1. Strategic transformation of competition in algorithmically mediated markets

Strategic dimension	Traditional market competition	Algorithmically mediated competition	Strategic implications for firms
Price formation	Periodic, managerially set, often visible, and comparatively stable	Continuous, automated, context-sensitive, and rapidly adjusted by algorithms	Firms must govern pricing logic strategically, rather than relying on periodic operational decisions
Competitive tempo	Response cycles are measured in days or weeks	Response cycles are measured in seconds or milliseconds	Strategic advantage depends on monitoring velocity and intervention readiness
Market visibility	Shaped by brand, shelf space, advertising, and search effort	Shaped by ranking models, recommendation systems, and platform exposure rules	Visibility management becomes a core competitive resource
Consumer demand formation	Influenced by relatively broad market signals and aggregate preferences	Influenced by individualized recommendations, behavioral inference, and attention allocation mechanisms	Demands become partially constructed by algorithmic systems rather than observed
Basis of rivalry	Product, price, quality, and brand differentiation	Algorithmic positioning, data quality, model responsiveness, and platform alignment	Firms compete through system architecture as much as through product attributes

Information symmetry	Rivals and managers often observe similar market signals	Signals are fragmented, personalized, and partially hidden within proprietary systems	Firms reduce competitive and benchmark visibility
Managerial control	Human managers retain direct authority over key decisions	Authority is delegated to semi-autonomous models, often with limited interpretability	Hybrid structures need prescriptive strategic advice
Learning mechanism	Post-period analysis, reporting, and episodic adjustment	Continuous retraining through behavioral data and outcome feedback loops	Advanced dependence on learning speed, feedback integration, and quality
Role of intermediaries	Often transactional or distributional	Architecturally central in setting ranking, data access, and competitive parameters	Platform dependence becomes a strategic condition and a periodic issue
Primary risk	Slow response, mispricing, or weak differentiation	Tacit coordination, opacity, over-automation, deskilling, and intermediary dependence	Rivalry management must emerge from recommendation algorithm governance
Source of sustained advantage	Scale, branding, product superiority, operational efficiency	Data intelligence, algorithm design, human-AI oversight, and adaptive governance	Complex durable competitive advantage requires governance of algorithmic layers and effectiveness

Academic research in strategic management and information systems journals has documented these shifts, highlighting both the efficiency gains and the competitive risks of algorithmic mediation [26-28]. Studies illustrate how recommendation algorithms can intensify rivalry by

broadening consumer search or, conversely, entrench market leaders through preferential visibility [4-6]. Parallel work on pricing algorithms reveals conditions under which independent agents converge on supra-competitive outcomes, underscoring the need for proactive risk management [1, 3, 10]. Platform-mediated environments add further complexity, as firms must navigate intermediary rules that govern data access and algorithmic parameters [13, 17, 18].

Strategic Challenge of Competition in Algorithmically Mediated Markets

Algorithmically mediated markets introduce structural challenges that fundamentally alter how firms price, position, and respond to rivals. Automated pricing systems compress decision cycles from days or weeks to milliseconds, enabling instantaneous reactions to competitor moves or demand fluctuations [1, 3, 9]. While this responsiveness can enhance efficiency, it also generates conditions conducive to tacit coordination. Independent pricing algorithms, trained on similar data and objectives, often converge on elevated prices without explicit communication, producing outcomes that mimic collusion and erode consumer welfare [1, 7, 10]. Managers must therefore grapple with the strategic paradox of deploying automation for competitive agility while guarding against unintended supra-competitive equilibria that invite regulatory scrutiny [11, 22].

Recommendation systems compound these challenges by functioning as active shapers of market visibility rather than neutral facilitators. By curating personalized product sets, these algorithms redistribute consumer attention and demand, often favoring firms with superior data inputs or platform compliance [4-6]. In duopolistic or oligopolistic settings, recommendation bias can intensify rivalry for algorithmic favor, prompting firms to optimize metadata, engagement signals, and content strategies not for intrinsic consumer value but for improved ranking within the platform's model [12, 13, 17]. Conversely, when recommendation engines reinforce historical preferences, they can entrench incumbents and fragment competition into isolated consumer clusters, diminishing the disciplining effect of broad market comparison [14, 27, 29]. The strategic implication is clear: visibility itself becomes a contested resource, and failure to manage

recommendation dynamics equates to ceding control over demand formation.

Data-driven interactions add opacity and personalization, further complicating competitive oversight. Firms now interact with consumers through individualized channels informed by continuous behavioral data streams, enabling granular pricing and offer customization [8, 15, 16]. Although this personalization can strengthen loyalty, it fragments the competitive landscape into microsegments, where traditional benchmarking against aggregate rivals becomes less relevant [17, 24]. Managers lose the shared market signals that once informed strategic moves, replaced instead by proprietary algorithmic inferences that are difficult to benchmark or contest [21, 23]. Platform intermediaries exacerbate this fragmentation by controlling data flows and algorithmic parameters, often limiting firm visibility into the very mechanisms that determine competitive outcomes [18, 19].

Algorithmic opacity compounds all these issues by fundamentally constraining the visibility of decision-making processes embedded within advanced computational systems. Many contemporary machine-learning models—particularly those based on deep learning architectures—function as high-dimensional black boxes, where the mapping between inputs and outputs is neither intuitively interpretable nor easily reconstructable *ex post*. As a result, managerial explanation of pricing or recommendation decisions becomes problematic not only for external stakeholders such as regulators and consumers, but also for internal governance structures tasked with ensuring accountability and strategic alignment [11, 22]. This lack of interpretability creates a critical asymmetry: firms rely on algorithmic outputs for operational decisions while simultaneously lacking a clear understanding of the causal mechanisms that drive them.

The implications for strategic control are substantial. Executives may observe anomalous or unexpected market outcomes—such as sudden shifts in demand, price convergence across competitors, or unexplained volatility in conversion rates—yet lack the diagnostic tools necessary to trace these effects back to specific algorithmic behaviors or data inputs [3, 7]. Without such causal traceability, timely and effective intervention becomes difficult, if not impossible. Consequently, firms risk adopting a reactive posture, responding to symptoms rather than addressing underlying systemic dynamics. Over time, this erodes the

capacity for deliberate strategy execution and weakens managerial authority over core competitive levers.

Regulatory accountability is similarly strained under conditions of algorithmic opacity. Competition authorities and legal frameworks are traditionally designed to assess intent, communication, and observable conduct among firms. However, when pricing or recommendation decisions originate from autonomous or semi-autonomous agents, attributing responsibility becomes significantly more complex [8, 23]. Firms may find themselves unable to demonstrate compliance with antitrust or consumer protection regulations, not because violations are intentional, but because the logic of decision-making is embedded in opaque models that resist straightforward explanation. This creates a paradox of accountability without transparency, in which firms are held responsible for outcomes they cannot fully explain.

At the same time, unintended coordination risks intensify. When competing firms deploy algorithms trained on similar datasets or exposed to comparable environmental signals—such as market prices, demand fluctuations, or platform ranking criteria—these systems may independently converge on parallel strategies. Such emergent alignment can resemble tacit collusion, even in the absence of direct communication or explicit coordination [1, 3, 10]. Because traditional legal thresholds for collusion rely on evidence of intent or agreement, these algorithmically mediated behaviors often fall into a gray zone that challenges existing enforcement mechanisms. The result is a competitive landscape in which coordination arises endogenously from shared data environments rather than from deliberate strategic interaction.

Taken together, these dynamics contribute to a broader transformation of competitive advantage. Traditional sources of differentiation—such as brand equity, product quality, and cost leadership—are increasingly mediated through algorithmic systems that determine visibility, pricing, and consumer engagement. In this environment, competitive success is less a function of intrinsic product attributes and more a function of how effectively those attributes are encoded, interpreted, and amplified by algorithms [5, 6, 13]. Data richness, interoperability with platform infrastructures, and the ability to continuously refine algorithmic models become critical determinants of performance, often superseding conventional strategic metrics.

This shift introduces the risk of strategic deskilling. As firms delegate a growing share of decision-making authority to automated systems, managerial capabilities related to pricing intuition, customer understanding, and competitive analysis may atrophy over time [21, 25]. Without deliberate efforts to maintain human oversight and interpretive capacity, organizations risk becoming overly dependent on algorithmic outputs, thereby reducing their ability to question, challenge, or override automated decisions. In extreme cases, this can lead to a form of organizational lock-in, where strategy is effectively dictated by system design rather than managerial intent.

To counteract these risks, firms must cultivate new managerial competencies centered on algorithmic governance. Such capabilities extend beyond technical proficiency to include the integration of monitoring systems, interpretability tools, and strategic foresight. Managers must be able to audit algorithmic behavior, identify deviations from strategic objectives, and intervene when necessary—all while ensuring compliance with regulatory and ethical standards. This requires the development of hybrid governance structures that combine data science expertise with traditional strategic management skills, enabling firms to preserve autonomy even as they operate within increasingly intermediated environments.

In essence, competition under algorithmic mediation is simultaneously faster, more opaque, and more interdependent than in pre-digital markets. Algorithms do not merely execute predefined strategies; they actively shape the conditions under which competition unfolds, influencing visibility, demand formation, and rival interactions in real time [2, 4, 27]. As such, they constitute not just operational tools but foundational elements of the competitive arena itself.

Managers must therefore move beyond reactive adjustments—such as incremental price changes or assortment tweaks—and instead adopt a proactive approach to the architecture of their algorithmic systems. This involves deliberate design choices regarding data inputs, model objectives, feedback mechanisms, and governance protocols, all of which influence how the firm competes and how it is perceived within platform ecosystems [11, 22]. Failure to engage at this architectural level risks ceding strategic initiative to external platforms and rival algorithms, effectively transforming once-autonomous firms into participants in a broader,

intermediated system where control is distributed, contingent, and continuously negotiated.

Building on this foundation, firms can transform the challenges of algorithmic mediation into sources of competitive advantage by adopting a structured strategic competition framework comprising five interdependent components. First, automated pricing capability must be designed with embedded safeguards, including simulation environments that stress-test algorithmic responses, deviation thresholds that trigger alerts when pricing behavior diverges from strategic intent, and periodic human review protocols to ensure alignment with broader objectives. These mechanisms enable firms to harness the speed and adaptability of dynamic pricing while mitigating risks associated with unintended coordination or regulatory non-compliance [1, 3, 7].

Second, recommendation and visibility management reframes platform algorithms as strategic assets rather than external constraints. Firms must continuously optimize the data signals they provide—such as product metadata, user engagement metrics, and content characteristics—to align with platform ranking logics. This requires an ongoing process of experimentation and refinement, as well as a deep understanding of how platform algorithms interpret and prioritize information [4–6].

Third, data acquisition and interaction intelligence focus on the systematic and ethical collection of consumer data that feeds both pricing and recommendation systems. Firms must develop capabilities to capture high-quality, granular interaction data while ensuring compliance with privacy regulations and maintaining consumer trust. The strategic value of data lies not only in its volume but also in its relevance, accuracy, and timeliness, all of which influence algorithmic performance [8, 15, 17].

Fourth, strategic monitoring and human oversight establish hybrid decision-making loops in which algorithms handle routine, high-frequency decisions. In contrast, human managers retain authority over exceptions, anomalies, and high-stakes choices. This dual structure ensures that automation enhances rather than replaces managerial judgment, preserving the organization's capacity for strategic reasoning and ethical evaluation [11, 21, 22].

Fifth, adaptive competitive response loops close the system by feeding market outcomes—such as changes in demand, competitor behavior, and platform dynamics—back into

Collectively, these components enable managers to compete through rather than merely with algorithmic systems. Practical implementation begins with capability audits that map existing pricing and recommendation tools against the framework, followed by targeted investments in simulation platforms and cross-functional oversight teams [7, 21]. To avoid blind reliance, organizations should institutionalize regular “algorithm stress tests” that expose systems to hypothetical rival moves or regulatory shifts, thereby preserving managerial agency [11, 22]. Strategic responses to platform intermediaries include proactive engagement on data-sharing terms and collaborative governance forums that influence algorithmic design parameters where feasible [13, 18, 19].

By embedding this architecture and framework, managers can respond strategically to algorithmic rivals: continuously refine capabilities, retain human judgment, and shape platform rules rather than merely react to them [21, 22]. The result is a resilient competitive posture that converts algorithmic mediation into a source of sustained advantage.

Having established the five-component strategic competition framework, firms must now operationalize these elements into concrete managerial capabilities. The transition from conceptual architecture to daily execution requires deliberate investment in hybrid human-AI systems that preserve strategic autonomy while leveraging algorithmic speed [7, 11, 22].

Automated pricing represents the most immediate level of competitive responsiveness, yet its deployment demands structured guardrails to prevent drift toward unintended coordination [1, 3, 10]. Managers should begin by commissioning internal simulation laboratories that test pricing algorithms against synthetic rival behaviors and demand shocks before live deployment [7, 9, 25]. These laboratories must incorporate deviation thresholds—predefined price floors, ceilings, and velocity limits—that trigger human review when algorithmic outputs deviate more than 15% from historical norms or strategic targets [11, 22]. Cross-functional pricing councils, comprising data scientists, marketers, and legal experts, should convene weekly to audit algorithm outputs for signs of parallel pricing patterns that could invite regulatory attention [1, 8, 23]. Practical implementation further requires modular algorithm design, allowing firms to swap in alternative objective functions (for example, market-share protection versus margin maximization) without full retraining, thereby preserving managerial flexibility in volatile platform environments [3, 18, 19].

Table 2 translates the five-component strategic competition framework into a managerial intervention matrix, specifying the objective, risk, governance lever, monitoring logic, and

organizational ownership associated with each capability domain.

Table 2. Managerial z intervention matrix for competing in algorithmically mediated markets

Framework component	Core strategic objective	Primary competitive risk	Managerial intervention
Automated pricing capability	Achieve rapid and strategically aligned price responsiveness	Emergent parallel pricing, uncontrolled price drift, and regulatory exposure	Simulate competitive response loops in a lab setting to understand the effects of rapid price changes on demand and regulatory risk exposure
Recommendation and visibility management	Secure favorable algorithmic exposure and demand access	Reduced discoverability, incumbent lock-in, and overdependence on platform ranking criteria	Monitor and experiment with metadata enhancements, user engagement prompts, and content formats to improve algorithmic favorability and diversify demand sources
Data acquisition and interaction intelligence	Build high-quality, decision-relevant, and ethically usable data assets	Data myopia, poor signal quality, privacy non-compliance, and trust erosion	Engage in proactive data-sharing alliances and joint governance workshops to influence the weighting of visibility parameters, converting potential dependency into negotiated influence
Strategic monitoring and human oversight	Preserve managerial authority over opaque algorithmic decisions	Black-box dependence, delayed anomaly detection, and strategic misalignment	Experiment with data pipelines that integrate first-party behavioral streams with ethically sourced third-party signals while maintaining granular consent records that satisfy evolving privacy regimes

Adaptive competitive response loops	Convert market outcomes into continuous strategic learning	Reactive behavior, misaligned retraining, and slow adaptation to rival or platform changes	Reactive competitive response loops
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Mastering recommendation and visibility management

Recommendation systems function as the primary channel for demand creation; therefore, visibility management must be elevated from a marketing tactic to a core strategic competence [4-6]. Firms should establish dedicated visibility optimization teams that monitor platform ranking signals in real time and systematically experiment with metadata enhancements, user-engagement prompts, and content formats to improve algorithmic favorability [12, 13, 17]. A/B testing protocols must be extended beyond consumer response to include rival-response forecasting: what happens to market share when a competitor's recommendation weight increases by 10% [5, 27]? To counter fragmentation risks, managers can deploy portfolio-level recommendation strategies that deliberately cross-promote complementary products across consumer clusters, thereby re-aggregating demand that platforms might otherwise silo [14, 29]. Platform intermediaries should be engaged proactively through data-sharing alliances and joint governance workshops that influence the weighting of visibility parameters, converting potential dependency into negotiated influence [13, 18, 19].

Enhancing data acquisition and interaction intelligence

Sustainable advantage in algorithmically mediated markets rests on superior data intelligence rather than raw volume [8, 15, 17]. Managers must build compliant data pipelines that integrate first-party behavioral streams with ethically sourced third-party signals while maintaining granular consent records that satisfy evolving privacy regimes [8, 15]. Interaction intelligence units should translate raw clickstream and preference data into predictive consumer micro-segments that feed both pricing and recommendation engines [16, 17]. To avoid data myopia, firms should institutionalize "data horizon scanning" exercises that periodically benchmark internal signals against platform-

wide trends, ensuring that personalization does not become overly insular [14, 27]. Ethical guardrails—algorithmic fairness audits conducted quarterly—prevent personalization from inadvertently reinforcing exclusionary patterns that could erode brand trust or trigger regulatory intervention [11, 15].

Implementing strategic monitoring and human oversight

The fourth capability—strategic monitoring—addresses the opacity challenge head-on by creating transparent oversight layers atop black-box models [21, 23, 24]. Firms should deploy explainable-AI dashboards that surface key decision drivers (feature importance scores, confidence intervals, counterfactual outcomes) for every high-impact pricing or recommendation event [11, 22]. Human oversight protocols must specify clear escalation triggers: any pricing adjustment exceeding a revenue-impact threshold or any recommendation list deviating from brand guidelines automatically routes to a designated executive for approval [7, 21]. Regular “algorithm red-team” exercises, in which internal teams simulate adversarial attacks on the firm’s own systems, sharpen both technical resilience and managerial intuition [24, 25]. This hybrid architecture ensures that algorithms execute routine operations while humans retain veto power over strategic anomalies, thereby restoring managerial control without sacrificing speed [11, 22].

Market-outcome data—share shifts, demand redistribution, and rival algorithmic signals—must be routed back into algorithm retraining pipelines on a daily or near-real-time cadence [24, 25, 27]. Adaptive response loops require dedicated competitive-intelligence platforms that ingest anonymized platform signals and translate them into actionable retraining inputs [18, 19]. Managers should institutionalize quarterly strategy recalibration workshops to assess whether current algorithmic parameters still align with overarching corporate objectives, and adjust objective functions as platform rules or rival behaviors evolve [5, 6]. By treating every competitive outcome as a learning signal, organizations convert the velocity of algorithmic markets into a self-reinforcing advantage rather than an uncontrollable force [25, 27].

Conclusion

Algorithmically mediated markets have permanently altered the foundations of rivalry. Pricing is no longer a periodic managerial act but a continuous, data-saturated dialogue among autonomous agents. Visibility is no longer earned solely through product excellence but through algorithmic fluency and platform alignment. Consumer interactions are no longer aggregate signals but individualized, real-time feedback loops that reshape demand formation moment by moment. In this environment, sustainable advantage accrues to organizations that treat algorithms as strategic co-actors requiring deliberate architecture, vigilant governance, and adaptive intelligence.

The five-component framework and the Competitive Architecture provide managers with a practical roadmap for converting mediation challenges into sources of differentiation. By investing in automated pricing guardrails, recommendation visibility mastery, ethical data intelligence, hybrid oversight, and closed-loop adaptation, firms can retain strategic agency amid accelerating automation. The result is not merely operational efficiency but a resilient competitive posture capable of navigating opacity, mitigating collusion risks, and shaping platform rules rather than merely reacting to them.

Ultimately, competition in algorithmically mediated markets rewards those who master the interplay between human judgment and machine speed. Executives who embed the framework presented here will be positioned to lead rather than follow in the next era of digital business strategy, turning algorithmic mediation into a durable source of advantage while safeguarding consumer welfare and regulatory compliance. The strategic mandate is clear: design the algorithms, govern the data flows, monitor the outcomes, and adapt relentlessly—or risk becoming a passive participant in markets shaped by others’ code.

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References

- Bichler M, Durmann J, Oberlechner M. Algorithmic Pricing and Algorithmic Collusion. *Bus Inf Syst Eng.* 2025. <https://doi.org/10.1007/s12599-025-00965-z>.
- Calvano E, Calzolari G, Denicolò V, Pastorello S. Artificial intelligence, algorithmic pricing, and collusion. *Am Econ Rev.* 2020;110(10):3267-97. <https://doi.org/10.1257/aer.20190623>.
- Gritsenko D, Wood M. Algorithmic governance: A modes of governance approach. *Regul Gov.* 2022;16(1):45-62. <https://doi.org/10.1111/rego.12367>.
- Clough DR, Wu A. Artificial intelligence, data-driven learning, and the decentralized structure of platform ecosystems. *Acad Manage Rev.* 2022;47(1):184-99. <https://doi.org/10.5465/amr.2020.0222>.
- Lu T, Wang Z, Wang J, Ai Q. A data-driven Stackelberg market strategy for demand response-enabled distribution systems. *IEEE Trans Smart Grid.* 2018;10(3):2345-57. <https://doi.org/10.1109/tsg.2018.2795007>.
- Jannach D, Jugovac M. Measuring the business value of recommender systems. *ACM Trans Manag Inf Syst.* 2019;10(4):1-23. <https://doi.org/10.1145/3370082>.
- Townley C, Morrison E, Yeung K. Big data and personalized price discrimination in EU competition law. *Yearb Eur Law.* 2017;36:244-88.
- Yablonsky S. AI-driven platform enterprise maturity: from human led to machine governed. *Kybernetes.* 2021;50(10):2753-89. <https://doi.org/10.1108/K-06-2020-0384>.
- Zhou B, Zou T. Competing for recommendations: The strategic impact of personalized product recommendations in online marketplaces. *Mark Sci.* 2023;42(2):280-302. <https://doi.org/10.1287/mksc.2022.1388>.
- Hansen KT, Misra K, Pai MM. Frontiers: Algorithmic collusion: Supra-competitive prices via independent algorithms. *Mark Sci.* 2021;40(1):1-12. <https://doi.org/10.1287/mksc.2020.1276>.
- Zhang J, Adomavicius G, Gupta A. Consumption and performance: Understanding longitudinal dynamics of recommender systems via an agent-based simulation framework. *Inf Syst Res.* 2020;31(1):76-101. <https://doi.org/10.1287/isre.2019.0876>.
- Fast V, Schnurr D, Wohlfarth M. Regulation of data-driven market power in the digital economy: Business value creation and competitive advantages from big data. *J Inf Technol.* 2023;38(2):121-42. <https://doi.org/10.1177/02683962221114394>.
- Breidbach CF, Maglio P. Accountable algorithms? The ethical implications of data-driven business models. *J Serv Manag.* 2020;31(6):1105-27. <https://doi.org/10.1108/JOSM-03-2019-0073>.
- Basukie J, Wang Y, Li S. Big data governance and algorithmic management in sharing economy platforms: A case of ridesharing in emerging markets. *Technol Forecast Soc Change.* 2020;161:120310. <https://doi.org/10.1016/j.techfore.2020.120310>.
- Rocher L, Tournier AJ, de Montjoye YA. Adversarial competition and collusion in algorithmic markets. *Nat Mach Intell.* 2023;5(7):724-33. <https://doi.org/10.1038/s42256-023-00646-0>.

Li L, Chen J, Raghunathan S. Recommender system rethink: Implications for an electronic marketplace with competing manufacturers. *Inf Syst Res.* 2018;29(4):1003-23.
<https://doi.org/10.1287/isre.2017.0765>.

Malgonde OS, Zhang H, Padmanabhan B. Managing digital platforms with robust multi-sided recommender systems. *Inf Syst Res.* 2022;33(1):267-87.
<https://doi.org/10.1080/07421222.2022.2127440>.

Li X, Grahl J, Hinz O. How do recommender systems lead to consumer purchases? A causal mediation analysis of a field experiment. *Inf Syst Res.* 2022;33(2):622-40.
<https://doi.org/10.1287/isre.2021.1074>.

Okeke NI, Alabi OA, Igwe AN, Ofodile OC. AI in customer feedback integration: A data-driven framework for enhancing business strategy. *World J Adv Res Rev.* 2024;15(3):1528-40.
<https://doi.org/10.30574/wjarr.2024.24.1.3207>.

Van Dijck J, Nieborg D, Poell T. Reframing platform power. *Internet Policy Rev.* 2019;8(2):1-18.
<https://doi.org/10.14763/2019.2.1414>.

Gai PJ, Klesse AK. Making recommendations more effective through framings: Impacts of user-versus item-based framings on recommendation click-throughs. *J Mark.* 2019;83(6):61-81.
<https://doi.org/10.1177/0022242919873901>.

Stucke ME. Should we be concerned about data-opolies? *Georget Law Technol Rev.* 2017;1(2):273-322.
<https://doi.org/10.2139/ssrn.3144045>.

Nuccio M, Guerzoni M. Big data: Hell or heaven? Digital platforms and market power in the data-driven economy. *Compet Change.* 2019;23(3):278-99.
<https://doi.org/10.1177/1024529418816525>.

Nitzberg M, Zysman J. Algorithms, data, and platforms: The diverse challenges of governing AI. *J Eur Public Policy.* 2022;29(10):1662-84.
<https://doi.org/10.1080/13501763.2022.2096668>.

Chen J, Dong H, Wang X, Feng F, Wang M, He X. Bias and debias in recommender system: A survey and future directions. *ACM Trans Inf Syst.* 2023;41(3):1-39.
<https://doi.org/10.1145/3564284>.

Bernhardt L, Dewenter R. Collusion by code or algorithmic collusion? When pricing algorithms take over. *Eur Compet J.* 2020;16(2-3):392-418.
<https://doi.org/10.1080/17441056.2020.1733344>.

Lee D, Hosanagar K. How do product attributes and reviews moderate the impact of recommender systems through purchase stages? *Manag Sci.* 2021;67(2):1142-62.
<https://doi.org/10.1287/mnsc.2019.3546>.

Larsson S. Algorithmic governance and the need for consumer empowerment in data-driven markets. *Internet Policy Rev.* 2018;7(2):1-12.
<https://doi.org/10.14763/2018.2.791>.

Lin Z, Goh KY, Heng CS. The Demand Effects of Product Recommendation Networks: An Empirical Analysis of Network Diversity and Stability. *MIS Q.* 2017;41(2):397-426.