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Algorithmic Pricing Intensity and the Curvilinear Reconfiguration of Consumer Fairness Norms

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Abstrak

Algorithmic pricing is widely framed as a technological instrument for efficiency and revenue optimization. Yet as pricing decisions become increasingly embedded within autonomous computational systems, their implications extend beyond performance outcomes to the normative foundations of market exchange. This article develops a conceptual framework explaining how algorithmic pricing intensity reshapes consumer fairness norms through curvilinear dynamics. Drawing on justice theory, reference price stability, attribution processes, and institutional legitimacy, the analysis proposes that algorithmic pricing intensity exhibits an inverted-U relationship with normative legitimacy. At low to moderate levels, algorithmic systems enhance procedural objectivity and enable adaptive updating of reference expectations, thereby strengthening fairness norms. Beyond a critical threshold, however, heightened volatility, granular personalization, and causal opacity destabilize reference anchors and intensify exploitative attributions, resulting in legitimacy erosion. By reframing fairness as a dynamic normative constraint rather than a static perception, the article contributes to research on digital market governance and strategic legitimacy, highlighting the bounded nature of algorithmic optimization in competitive digital environments

Keywords

algorithmic pricing intensity; normative legitimacy; price fairness; procedural justice; digital market governance; curvilinear effects

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1. Introduction

Pricing has long occupied a central position in strategic management and marketing theory because it represents the most direct interface between firm value capture and consumer evaluation. Classical perspectives treat pricing as a balancing mechanism between cost structures, competitive positioning, and perceived customer value. In digital markets, however, pricing is no longer primarily a managerial decision executed periodically; it has become an ongoing computational process embedded in algorithmic infrastructures. Increasingly, prices are adjusted in real time, differentiated across individuals, and optimized through predictive analytics. Algorithmic pricing systems calibrate price levels using demand signals, behavioral data, and predictive analytics, transforming pricing from a discrete managerial act into a continuous computational function.

This transformation has been largely framed as an efficiency-enhancing innovation. Research in digital transformation and AI-enabled marketing emphasizes personalization accuracy, dynamic responsiveness, and revenue optimization as key benefits of algorithmic systems (Verhoef et al., 2021; Kumar et al., 2024). Within this logic, pricing algorithms are portrayed as rational instruments that reduce human bias, enhance allocative efficiency, and improve market matching. From a managerial standpoint, higher levels of algorithmic intensity promise superior margin management and competitive agility. Consequently, the strategic discourse surrounding algorithmic pricing has predominantly centered on performance outcomes and optimization potential.

Yet the diffusion of algorithmic pricing has also generated increasing controversy. Public debates around surge pricing, personalized price discrimination, and opaque digital markups reveal recurring consumer backlash. Empirical studies document that dynamic pricing can trigger perceptions of unfairness, particularly when price changes are rapid, individualized, or insufficiently explained (Haws & Bearden, 2006; Xia et al., 2004). More recent work indicates that algorithmic mediation may intensify these reactions when consumers attribute price differences to profiling or hidden data usage rather than to transparent cost factors (Rai & Sinha, 2023). These reactions suggest that pricing is not evaluated solely through economic rationality but through normative frameworks of fairness and legitimacy.

Existing fairness research, however, remains largely perception-centered. Foundational studies conceptualize price fairness as an evaluative judgment shaped by distributive comparisons, procedural consistency, and attributional reasoning (Xia et al., 2004; Bolton et al., 2003). Distributive justice emphasizes outcome equality or equity, whereas procedural justice highlights the fairness of the rule or process generating outcomes. While this body of work offers valuable insights into consumer reactions, it typically assumes a linear relationship between pricing practices and fairness perceptions: greater deviation from reference expectations leads to lower fairness evaluations. Such models implicitly treat fairness as an immediate psychological response rather than as a dynamic, evolving normative structure.

Algorithmic pricing challenges this linear assumption. At moderate levels, automated pricing may signal objectivity and consistency, thereby enhancing perceptions of procedural fairness. Algorithms can be interpreted as neutral rule-following systems that reduce arbitrary human intervention, potentially strengthening legitimacy. At higher levels of intensity, however, increased volatility, granular personalization, and causal opacity may undermine consumers' ability to form stable reference prices and interpret pricing logic. When price formation becomes difficult to predict or justify, fairness evaluations may deteriorate sharply. These opposing tendencies suggest that the relationship between algorithmic pricing intensity and fairness legitimacy may be curvilinear rather than linear.

Despite growing scholarly interest in algorithmic decision-making and digital market governance (Raisch & Krakowski, 2021; Shrestha et al., 2019), little attention has been devoted to theorizing how increasing algorithmic intensity reshapes the normative architecture of pricing itself. Fairness has rarely been conceptualized as a shared market norm that constrains legitimate conduct. Instead, it is often operationalized as an individual-level perception affecting satisfaction or purchase intention. This limitation obscures an important strategic dimension: when fairness concerns become collectively salient, they influence firm reputation, regulatory scrutiny, and competitive dynamics. In such contexts, fairness functions not merely as a consumer attitude but as a normative boundary that defines acceptable pricing behavior.

This article addresses that gap by developing a conceptual framework that reconceptualizes fairness under algorithmic pricing as a normative construct shaped by curvilinear dynamics. Drawing on justice theory, reference price theory, and attribution theory, the analysis proposes that algorithmic pricing intensity exhibits an inverted-U relationship with the normative legitimacy of pricing conduct. At low to moderate levels, algorithmic systems enhance procedural clarity and efficiency signals, allowing consumers to update fairness norms within an expanded range of acceptable variation. Beyond a threshold, however, heightened volatility, granular personalization, and causal opacity destabilize reference anchors and intensify suspicion, triggering normative backlash.

By shifting the analytical focus from fairness perception to fairness norms, this study advances three contributions. First, it reframes pricing fairness as a dynamic normative architecture rather than as a static evaluative response. Second, it introduces curvilinear logic into the study of algorithmic pricing legitimacy, specifying the mechanisms that generate both legitimacy gains and legitimacy erosion. Third, it integrates procedural justice with institutional perspectives on market conduct, highlighting how fairness norms evolve and potentially become codified in digital markets.

In doing so, the article contributes to the broader literature on digital market governance and strategic legitimacy by demonstrating that algorithmic intensity is not merely a technical variable but a normative force. As pricing becomes increasingly automated, firms face not only optimization challenges but legitimacy thresholds. Understanding when algorithmic pricing strengthens or weakens fairness norms is therefore essential for explaining both strategic advantage and reputational risk in contemporary digital competition. Specifically, the article develops a mechanism-based framework explaining how algorithmic pricing intensity reshapes fairness norms through a curvilinear legitimacy dynamic.

2. Literature Review (Theoretical Foundations)

The theoretical development of this article requires integrating four streams of scholarship that have largely evolved independently: price fairness and justice theory, reference price and expectation stability research, attribution theory in pricing contexts, and institutional perspectives on market legitimacy. While each stream offers insight into how consumers evaluate pricing practices, none fully explains how increasing algorithmic intensity restructures fairness as a shared market norm. Bringing these literatures into conversation enables a shift from perception-based explanations to a norm-based, curvilinear account of pricing legitimacy in digital markets.

2.1 Price Fairness and Justice Theory: From Outcome Evaluation to Procedural Legitimacy

Price fairness research has traditionally conceptualized fairness as an evaluative judgment formed through social comparison and equity considerations. Early work grounded in distributive justice theory argues that consumers assess fairness by comparing outcomes across transactions or individuals (Bolton et al., 2003; Xia et al., 2004). When price differences are perceived as disproportionate or discriminatory, distributive injustice is inferred. This approach emphasizes outcome parity and relative comparison as primary fairness determinants.

However, subsequent scholarship highlights that consumers also evaluate the fairness of the process generating the outcome. Procedural justice theory posits that fairness judgments depend not only on the magnitude of a price difference but also on whether the pricing rule appears consistent, unbiased, and morally appropriate (Thibaut & Walker, 1975; Lind & Tyler, 1988). In pricing contexts, procedural fairness concerns whether firms apply coherent criteria, avoid opportunism, and adhere to socially acceptable norms (Bolton et al., 2003). Consumers may tolerate price increases if they are perceived as cost-justified, but react negatively when increases appear arbitrary or exploitative.

This distinction between distributive and procedural justice becomes particularly salient in algorithmic pricing environments. Algorithms introduce new rule structures that may be perceived as either neutral and objective or opaque and manipulative. While distributive outcomes (e.g., paying more than another customer) remain important, procedural legitimacy increasingly governs overall fairness judgments. In digital markets where prices fluctuate rapidly, consumers cannot easily observe comparative outcomes; instead, they infer fairness from perceived rule integrity.

Despite this theoretical richness, existing models largely assume monotonic effects: deviations from reference expectations reduce fairness. Few studies theorize how procedural perceptions might initially improve under moderate automation before deteriorating at higher levels of algorithmic intensity. Consequently, justice theory provides conceptual tools but lacks a dynamic framework explaining how legitimacy evolves as pricing systems intensify.

2.2 Reference Price Stability and Expectation Anchoring

Reference price theory further illuminates the cognitive foundation of fairness judgments. Consumers maintain internal or external reference points that serve as anchors for evaluating current prices (Kalyanaram & Winer, 1995). Deviations from these anchors generate gain or loss perceptions, influencing satisfaction and fairness evaluations. Reference prices function not only as economic benchmarks but also as normative expectations about what constitutes a “reasonable” price.

Stability plays a crucial role in maintaining reference integrity. When price variations remain within predictable ranges, consumers update their expectations gradually. However, excessive volatility disrupts anchoring processes, leading to uncertainty and diminished fairness perceptions. Research on dynamic pricing suggests that unpredictable or frequent fluctuations can erode trust even when average price levels remain competitive (Haws & Bearden, 2006).

Algorithmic pricing intensifies this dynamic. High-frequency adjustments and granular differentiation may prevent consumers from forming stable anchors. Without a coherent reference point, fairness evaluation shifts from outcome comparison to process interpretation. Consumers begin asking not “Is this price high?” but “Why is this price different now?” This shift signals a movement from distributive assessment toward procedural scrutiny.

Importantly, reference price disruption does not occur uniformly across all levels of algorithmic deployment. At moderate levels, algorithmic adjustments may remain within acceptable normative bandwidths, allowing reference updating without anchor collapse. At higher intensities, volatility may exceed consumers’ adaptive capacity, producing fairness instability. This non-linear adaptation logic forms a critical component of the proposed curvilinear model.

2.3 Attribution Theory and Causal Interpretation in Algorithmic Pricing

Attribution theory provides a mechanism explaining how consumers interpret price changes under uncertainty. Individuals seek causal explanations for observed outcomes, especially when outcomes deviate from expectations (Heider, 1958). In pricing contexts, consumers attribute price differences either to legitimate cost drivers (e.g., demand surges, supply constraints) or to opportunistic firm behavior (Xia et al., 2004). These attributions mediate fairness judgments.

Algorithmic pricing complicates causal inference. When price formation is embedded in complex data-driven systems, the decision rule becomes less visible. Consumers may struggle to identify whether price differences reflect objective conditions or personalized profiling. Research on algorithmic decision-making indicates that opacity increases suspicion and reduces perceived legitimacy (Rai & Sinha, 2023). Conversely, transparent explanation can mitigate negative reactions by restoring causal clarity.

At moderate levels of algorithmic use, automation may be interpreted as neutral rule application, reducing suspicions of human opportunism. Algorithms can be perceived as consistent and impartial. As algorithmic intensity increases—particularly through highly individualized pricing—attribution shifts from objectivity to exploitation. Consumers may infer that hidden data signals are being used against them, intensifying perceptions of procedural injustice.

Thus, attribution processes help explain the tipping point in the inverted-U relationship. When causal interpretation transitions from "objective system" to "manipulative mechanism," legitimacy declines sharply. The shift is not driven solely by price magnitude but by perceived intentionality embedded in opaque computational processes.

2.4 From Individual Perceptions to Normative Architecture: Institutionalizing Fairness

While justice, reference, and attribution theories explain individual-level fairness judgments, they do not fully capture how these judgments evolve into collective norms. Institutional theory suggests that repeated evaluative patterns can crystallize into shared expectations regarding legitimate conduct (Suchman, 1995). Legitimacy arises when organizational practices align with socially constructed norms and values. In digital markets, pricing conduct is increasingly scrutinized within broader discourses about algorithmic transparency, discrimination, and market power.

When fairness concerns become publicly salient, they move beyond individual dissatisfaction. Media narratives, regulatory debates, and consumer advocacy can transform perceived unfairness into codified expectations. Under such conditions, pricing practices are evaluated not merely through economic efficiency but through moral and institutional criteria. Fairness norms thus operate as boundary conditions constraining strategic action.

Algorithmic pricing intensity may accelerate this institutionalization process. Highly granular and opaque pricing increases the likelihood of collective backlash, especially in morally sensitive product categories. As scrutiny intensifies, legitimacy becomes contingent on governance mechanisms, disclosure policies, and procedural safeguards. Fairness, in this context, evolves from a subjective reaction into a normative standard shaping competitive conduct.

This institutional dimension underscores the need to reconceptualize fairness under algorithmic pricing as a dynamic normative structure. The literature provides fragmented insights into distributive outcomes, procedural perceptions, and attribution mechanisms, yet lacks an integrated model explaining how increasing algorithmic intensity produces curvilinear shifts in legitimacy. Addressing this gap requires synthesizing these streams into a unified framework specifying both enabling and eroding mechanisms.

Together, these theoretical foundations establish three core premises:
1) fairness in pricing is strongly influenced by procedural legitimacy rather than solely distributive outcomes;
2) stability of reference expectations is essential for normative acceptance; and
3) causal attribution under opacity conditions mediates legitimacy judgments.

Building on these premises, the next section develops a conceptual model proposing that algorithmic pricing intensity generates a curvilinear reconfiguration of consumer fairness norms through interacting efficiency, volatility, personalization, and opacity mechanisms.

The following table consolidates the article's theoretical propositions into a structured analytical overview. Presenting the propositions in tabular form helps readers and reviewers clearly identify the core relationships, mechanisms, and theoretical logic underlying the conceptual model. This format ensures that the argument remains parsimonious while preserving the mechanism-driven structure developed throughout the conceptual section.

Table 1. Architecture of Theoretical Propositions

Proposition	Core Relationship	Underlying Mechanism
P1	Algorithmic Pricing Intensity → Normative Legitimacy (positive at low–moderate levels)	Automation signals rule-based objectivity and reduces perceptions of human opportunism.
P2	API → Normative Legitimacy (mediated)	Procedural objectivity and adaptive reference price updating strengthen legitimacy.
P3	Pricing Volatility → Normative Legitimacy (negative)	Excessive price fluctuation destabilizes reference price anchors.
P4–P5	Personalization and Opacity → Normative Legitimacy (negative)	Granular differentiation and opaque pricing rules intensify exploitative causal attributions.
P6–P10	Contextual Moderation of API–Legitimacy Relationship	Product moral salience, market transparency, disclosure regimes, and algorithmic literacy shift the legitimacy threshold.

Source: Developed by the author

Table 1 organizes the article's propositions into a coherent analytical structure that links the curvilinear core relationship with its underlying mechanisms and contextual moderators. By consolidating the propositions, Table 1 clarifies how the theoretical argument progresses from legitimacy expansion under moderate algorithmic integration to legitimacy erosion once interpretive thresholds are exceeded. This structured overview supports readers in tracing how each proposition contributes to the overall curvilinear theory of algorithmic pricing legitimacy.

3. Conceptual Development

Building on justice theory, reference price stability, attribution processes, and institutional legitimacy, this section develops a mechanism-driven explanation of how algorithmic pricing intensity reshapes consumer fairness norms. Instead of framing algorithmic pricing as a uniform technological innovation, the phenomenon is conceptualized as a progressive reallocation of decision authority and interpretive visibility within pricing governance structures. As organizations deepen algorithmic integration, pricing becomes increasingly detached from visible managerial discretion and embedded within opaque computational infrastructures. This transformation alters not only price levels but also the interpretive conditions under which fairness judgments are formed.

3.1 Algorithmic Pricing Intensity as Governance Depth

Algorithmic pricing intensity (API) refers to the degree to which pricing decisions are autonomously generated, recalibrated, and executed by computational systems rather than by human managers. Delegation to algorithms does not merely increase operational efficiency; it restructures decision authority and interpretive accountability (Raisch & Krakowski, 2021; Shrestha et al., 2019). As research on algorithmic management demonstrates, automation transforms how control is exercised and how decisions are justified (Kellogg et al., 2020).

API therefore represents governance depth: the extent to which pricing logic is embedded within self-updating computational routines operating with limited human oversight (Lebovitz et al., 2022). This governance depth manifests along four interrelated dimensions—volatility, granularity, autonomy, and opacity. These dimensions jointly shape how consumers interpret the legitimacy of pricing conduct. Importantly, responses to algorithmic systems are intensity-dependent rather than uniform (Castelo et al., 2019; Puntoni et al., 2021), suggesting that legitimacy effects vary across increasing levels of algorithmic integration.

The following table clarifies the conceptual structure of Algorithmic Pricing Intensity (API) by identifying its core dimensions and explaining how each manifests within digital pricing systems. Providing this structured definition is important because API represents the foundational construct of the article; understanding its dimensions allows readers to interpret the subsequent theoretical model and propositions more precisely.

Table 2. Dimensions of Algorithmic Pricing Intensity

Dimension	Conceptual Definition	Pricing Manifestation
Volatility	The frequency and magnitude with which algorithmic systems update price levels in response to market signals.	Continuous or high-frequency price adjustments based on real-time demand, inventory levels, or behavioral signals.
Granularity	The degree to which prices are differentiated across individuals, segments, or contexts.	Personalized or micro-segmented pricing based on user data, browsing behavior, or inferred willingness to pay.
Autonomy	The extent to which pricing decisions are generated and executed by computational systems without direct managerial intervention.	Automated price setting through machine-learning models that recalibrate prices without manual approval.
Opacity	The degree to which the logic underlying price formation is difficult for external observers to interpret or verify.	Black-box pricing algorithms where the determinants of price changes are not transparent to consumers or regulators.

Source: Developed by the author

Table 2 systematizes the construct of algorithmic pricing intensity by decomposing it into four analytically distinct yet interrelated dimensions. This structure clarifies how API represents the depth of algorithmic governance in pricing decisions. By specifying how volatility, granularity, autonomy, and opacity manifest in pricing systems, the table provides a conceptual foundation for interpreting the curvilinear legitimacy dynamics developed later in the article.

3.2 The Upward Legitimacy Phase: Procedural Expansion Under Moderate Intensity

At low to moderate levels of API, algorithmic pricing may enhance normative legitimacy by expanding procedural fairness perceptions. Consumers frequently attribute objectivity and analytical competence to computational systems—a phenomenon described as the machine heuristic (Sundar & Kim, 2019). Under such conditions, algorithmic intervention may be interpreted as systematic rule execution rather than managerial opportunism.

When price adjustments appear data-driven and demand-responsive, procedural justice perceptions strengthen because the pricing rule seems impersonal, coherent, and disciplined (Bolton et al., 2003). Research on trust in AI further suggests that algorithmic systems may initially command confidence when framed as analytical and unbiased (Glikson & Woolley, 2020). In this early phase, automation does not destabilize fairness norms; it may expand them.

Reference price theory reinforces this logic. Consumers possess adaptive capacity (Kalyanaram & Winer, 1995), and moderate volatility does not necessarily disrupt fairness evaluation. Instead, when variation remains within predictable and interpretable bounds, consumers recalibrate expectations (Mazumdar et al., 2005). Algorithmic pricing that remains within such bounds becomes normalized as legitimate modernization of pricing conduct.

Taken together, these arguments imply that increasing algorithmic intensity initially strengthens procedural legitimacy and broadens the acceptable bandwidth of price variation.

Proposition 1. At low to moderate levels of algorithmic pricing intensity, increases in API are positively associated with the normative legitimacy of pricing conduct.

Proposition 2. The positive association between API and normative legitimacy in this phase is mediated by (a) perceived procedural objectivity and (b) adaptive reference price updating.

3.3 Normative Reversal: When Intensity Undermines Legitimacy

Beyond a critical threshold, however, the very mechanisms that previously enhanced legitimacy begin to erode it. As volatility intensifies, granularity deepens, and opacity thickens, interpretive stability weakens. Legitimacy declines not because algorithmic pricing ceases to be systematic, but because it exceeds consumers' interpretive tolerance.

The following diagram isolates the mechanisms responsible for legitimacy erosion when algorithmic pricing intensity exceeds the interpretive tolerance of consumers. Rather than depicting the overall model, the structure focuses specifically on the causal pathways through which volatility, granular personalization, and opacity destabilize fairness norms and trigger declining legitimacy in digital pricing environments.

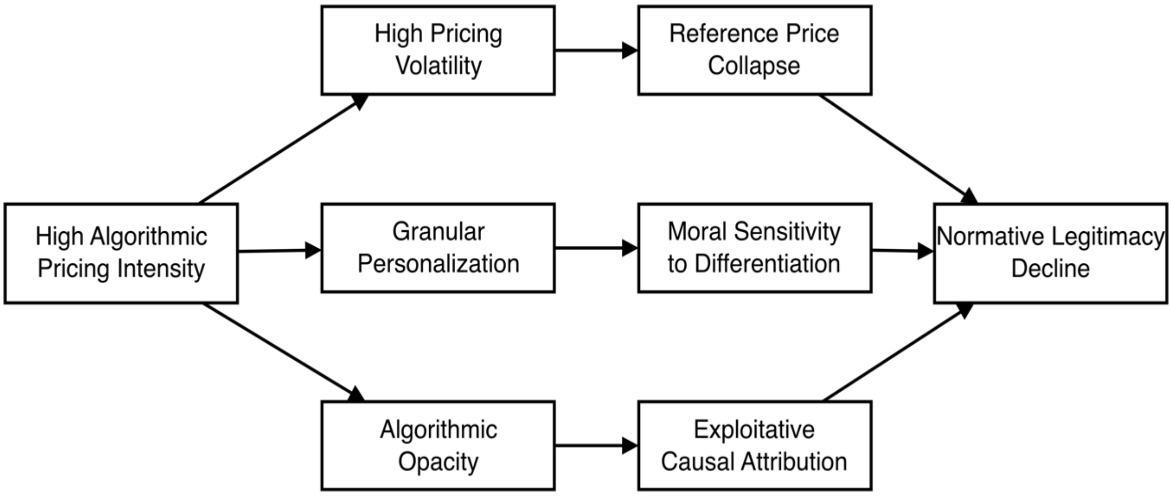

Figure 1. Mechanisms of Normative Legitimacy Erosion Under High Algorithmic Pricing Intensity
Source: Author's conceptualization.

Figure 1 disaggregates the processes through which high levels of algorithmic pricing intensity undermine the legitimacy of pricing conduct. As illustrated in Figure 1, elevated algorithmic integration simultaneously increases pricing volatility, granular personalization, and algorithmic opacity. Each mechanism generates a distinct interpretive response: volatility destabilizes reference price anchors, personalization activates moral scrutiny of differentiation criteria, and opacity intensifies exploitative causal attributions. The convergence of these mechanisms ultimately produces declining normative legitimacy once algorithmic pricing exceeds consumers' interpretive tolerance.

Volatility and Reference Collapse

Excessive volatility disrupts anchor formation. High-frequency recalibration may overwhelm consumers' ability to construct coherent reference points, producing reference collapse (Haws & Bearden, 2006; Xia et al., 2004). In such conditions, fairness evaluation shifts from comparative reasoning to suspicion-based inference. The pricing rule appears unstable—even if internally consistent—because experiential predictability is lost.

Proposition 3. High levels of pricing volatility weaken reference price stability, which in turn reduces normative legitimacy of pricing conduct.

Granularity and Moral Sensitivity

As personalization becomes increasingly granular, consumers evaluate not merely price differences but the moral grounds underlying differentiation. Research on algorithmic bias and ethical AI indicates that personalized decisions trigger fairness concerns when differentiation appears discriminatory or exploitative (Lambrecht & Tucker, 2019; Martin, 2019). Algorithm aversion intensifies when decision criteria are perceived as morally intrusive (Castelo et al., 2019; Longoni et al., 2019).

Granular pricing based on inferred willingness to pay may therefore cross perceived moral boundaries. In this phase, legitimacy erosion is driven less by price magnitude than by the perceived impropriety of differentiation criteria.

Proposition 4. The relationship between personalization granularity and normative legitimacy is negatively moderated by perceived moral inappropriateness of differentiation grounds, such that legitimacy declines more sharply when differentiation criteria are judged morally questionable.

Opacity and Suspicion Escalation

Opacity amplifies destabilization. When pricing logic becomes interpretively inaccessible, consumers are more likely to attribute exploitative intent (Araujo et al., 2020; Rader & Gray, 2015). The black-box character of algorithmic systems obscures accountability (Pasquale, 2015), intensifying dispositional attributions of unfairness (Heider, 1958).

Opacity thus accelerates legitimacy erosion beyond the threshold.

Proposition 5. Algorithmic opacity strengthens the negative relationship between high API and normative legitimacy by increasing exploitative causal attributions.

3.4 The Curvilinear Legitimacy Dynamic

Synthesizing these mechanisms, algorithmic pricing intensity is theorized to exhibit an inverted-U relationship with normative legitimacy. At moderate levels, algorithmic pricing enhances procedural objectivity and supports adaptive reference updating. Beyond a threshold, volatility-induced reference collapse, morally sensitive personalization, and opacity-driven suspicion become dominant, resulting in legitimacy erosion.

The conceptual model below integrates the article's theoretical mechanisms to explain how algorithmic pricing intensity reshapes the legitimacy of pricing conduct. The framework distinguishes between mechanisms that initially expand legitimacy—through perceived procedural objectivity and adaptive reference updating—and mechanisms that later erode legitimacy when algorithmic intensity becomes excessive. By mapping these parallel processes, the model clarifies the theoretical architecture underlying the curvilinear relationship developed.

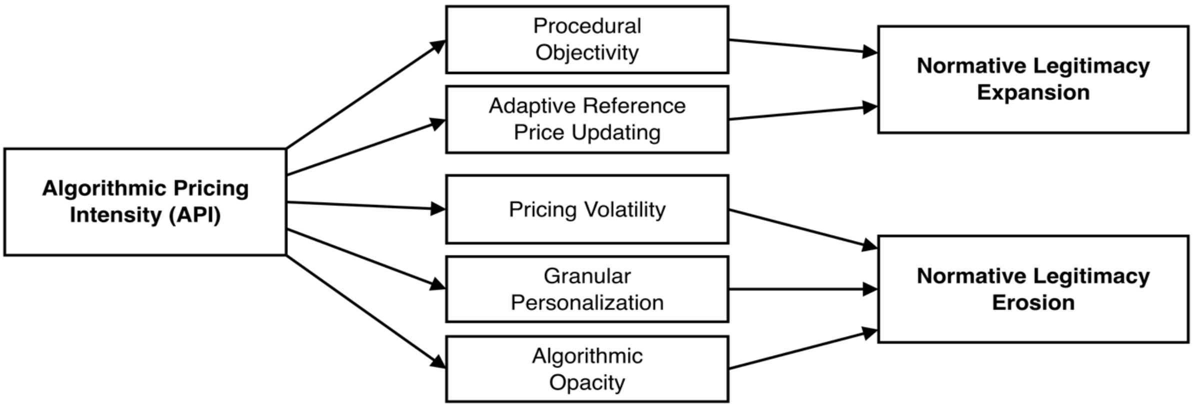

Figure 2. Conceptual Framework of Algorithmic Pricing Intensity and Normative Legitimacy
Source: Author's conceptualization.

Figure 2 organizes the theoretical mechanisms explaining how algorithmic pricing intensity reshapes fairness norms in digital markets. The upper pathway illustrates the legitimacy-expanding phase in which moderate algorithmic integration strengthens perceived procedural objectivity and enables adaptive reference price updating, thereby enhancing normative legitimacy. The lower pathway captures the legitimacy-erosion phase that emerges when algorithmic intensity increases further, generating volatility, granular personalization, and opacity that undermine interpretive stability. By structuring these mechanisms within a single framework, Figure 2 clarifies how the same technological system can both reinforce and destabilize fairness norms depending on the level of algorithmic integration.

This curvilinear dynamic aligns with emerging evidence of non-linear trust and aversion patterns in algorithmic decision contexts (Castelo et al., 2019; Raisch & Krakowski, 2021). It extends fairness theory by introducing intensity-dependent normative thresholds rather than static evaluative responses.

Proposition 6. Algorithmic pricing intensity exhibits an inverted-U relationship with the normative legitimacy of pricing conduct.

The diagram below visualizes the curvilinear relationship proposed in the article between algorithmic pricing intensity and the normative legitimacy of pricing conduct. The structure emphasizes that legitimacy does not change monotonically with increasing automation. Instead, moderate algorithmic integration expands procedural legitimacy, whereas excessive intensity destabilizes fairness norms and produces legitimacy erosion beyond a critical threshold.

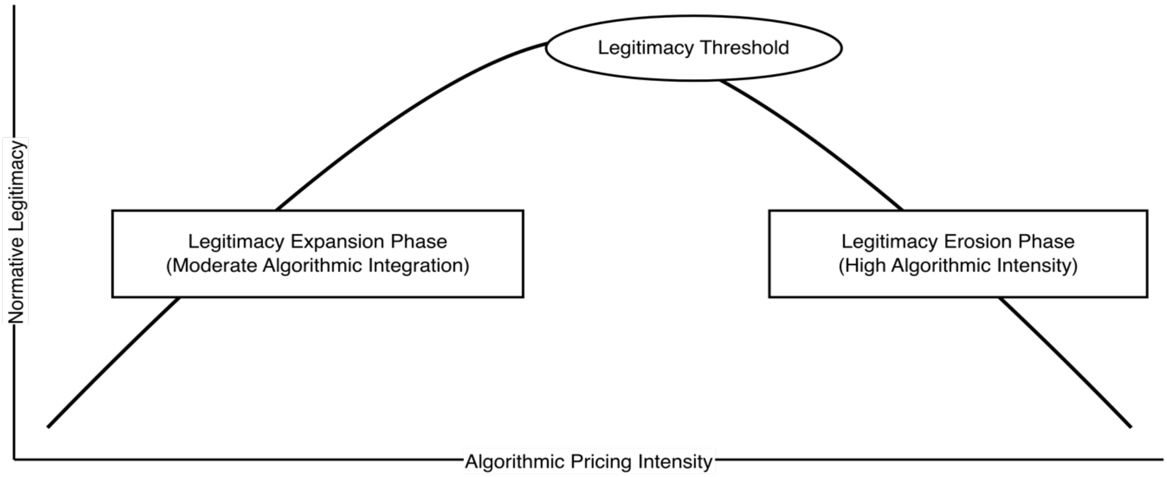

Figure 3. Curvilinear Relationship Between Algorithmic Pricing Intensity and Normative Legitimacy
Source: Author's conceptualization.

Figure 3 presents the central theoretical relationship developed in the article: the inverted-U association between algorithmic pricing intensity and the normative legitimacy of pricing conduct. As algorithmic integration increases from low to moderate levels, legitimacy expands because pricing systems appear more objective and procedurally consistent. The peak of the curve represents the legitimacy threshold, beyond which further increases in algorithmic intensity destabilize reference expectations and heighten suspicion regarding personalization and opacity. Consequently, legitimacy declines as algorithmic pricing becomes excessively volatile and interpretively opaque.

3.5 Contextual Moderators of the Legitimacy Threshold

The legitimacy threshold is context-dependent. In morally salient product categories, tolerance for personalization and volatility is lower (Longoni et al., 2019). In highly transparent markets, cross-comparison accelerates fairness sensitivity (Burtch et al., 2018). Disclosure regimes further moderate outcomes: explanation may mitigate suspicion when grounded in accepted justifications, yet exacerbate backlash when it reveals morally questionable criteria (Andrews, 2021). Consumer algorithmic literacy also shapes interpretive orientation (Araujo et al., 2020).

Proposition 7. The inverted-U relationship between API and normative legitimacy shifts leftward in morally salient product categories.

Proposition 8. Market transparency lowers tolerance for algorithmic differentiation, accelerating legitimacy reversal.

Proposition 9. Procedurally justified disclosure attenuates legitimacy erosion at high levels of API.

Proposition 10. Consumer algorithmic literacy moderates the curvilinear relationship between API and legitimacy, amplifying either legitimacy gains or losses depending on attributional orientation.

4. Discussion

This article advances a curvilinear theory of algorithmic pricing legitimacy by situating pricing automation within broader debates on fairness, governance, and institutional stability. While prior research has tended to frame algorithmic pricing either as an efficiency-enhancing mechanism or as a fairness-threatening innovation, the present analysis demonstrates that both interpretations are conditionally valid. Legitimacy does not decline monotonically with automation, nor does it increase indefinitely with procedural standardization. Instead, algorithmic pricing intensity restructures the normative architecture of fairness in threshold-dependent ways.

4.1 Reframing Fairness Under Algorithmic Governance

Price fairness research has historically conceptualized fairness as an evaluative response shaped by distributive comparison and procedural assessment (Bolton et al., 2003; Xia et al., 2004). Within this tradition, deviations from reference expectations typically produce proportional declines in fairness perception. Even when procedural justice is incorporated, the underlying logic remains largely linear: more deviation or inconsistency yields lower fairness.

However, algorithmic pricing challenges this monotonic assumption. Research on AI-enabled decision-making shows that algorithmic systems can initially be perceived as more objective and less biased than human agents (Glikson & Woolley, 2020; Sundar & Kim, 2019). These findings suggest that automation may enhance procedural legitimacy under certain conditions. Yet parallel streams of research document algorithm aversion and fairness backlash when decisions become opaque or morally intrusive (Castelo et al., 2019; Longoni et al., 2019).

The coexistence of these findings reveals a theoretical tension in the literature: automation simultaneously promises objectivity and triggers suspicion. Rather than treating these streams as contradictory, the present framework integrates them through an intensity-based explanation. Moderate algorithmic integration expands procedural fairness by signaling rule-based consistency and adaptive responsiveness. Beyond a threshold, increased volatility, granular personalization, and opacity destabilize reference anchors and intensify exploitative attribution. Fairness norms thus evolve rather than simply weaken.

This shift from perception to normative architecture extends justice theory in two ways. First, it introduces temporal and structural dynamics into fairness evaluation, suggesting that fairness expectations adapt and then contract depending on algorithmic depth. Second, it embeds procedural justice within institutional legitimacy processes (Suchman, 1995), demonstrating how repeated interpretive patterns can crystallize into shared norms constraining pricing conduct. Fairness becomes not merely a cognitive judgment but a boundary condition of legitimate market behavior.

4.2 Legitimacy Thresholds and the Paradox of Algorithmic Optimization

A central implication of the inverted-U model is the existence of legitimacy thresholds. Digital transformation literature frequently portrays algorithmic optimization as an unqualified improvement in efficiency and decision quality (Raisch & Krakowski, 2021; Huang & Rust, 2021). Yet this performance-centric framing overlooks the possibility that optimization may undermine its own normative foundations.

The curvilinear logic identifies a structural paradox: mechanisms that enhance allocative efficiency at moderate levels—real-time responsiveness, predictive personalization, automated adjustment—may erode legitimacy when intensified. Excessive volatility disrupts reference stability (Haws & Bearden, 2006), granular differentiation activates moral scrutiny (Lambrecht & Tucker, 2019), and opacity amplifies exploitative attribution (Araujo et al., 2020). Efficiency gains therefore coexist with legitimacy risks.

This paradox extends algorithmic governance research by linking automation depth to normative sustainability. Prior scholarship has examined algorithmic control, decision delegation, and AI–human integration primarily from organizational or performance perspectives. The present framework adds a legitimacy dimension: algorithmic intensity is strategically bounded not only by technical capability but by normative tolerance. Firms that exceed interpretive thresholds risk reputational damage and regulatory scrutiny, even when pricing algorithms remain economically rational.

Thus, optimization without normative calibration is unstable. Sustainable digital competition requires alignment between computational sophistication and socially accepted fairness standards.

4.3 Procedural Justice as the Core Mechanism of Digital Pricing Legitimacy

In computational markets characterized by rapid and individualized price variation, distributive comparison becomes increasingly difficult. Consumers often lack visibility into what others pay, limiting direct outcome comparison. Under such conditions, procedural interpretation becomes the primary fairness lens. Consumers evaluate whether the pricing rule appears coherent, justified, and morally defensible rather than whether the price equals another's.

This re-centering of procedural justice carries theoretical implications. While classical fairness models treat distributive and procedural components as complementary, algorithmic pricing environments elevate procedural evaluation to a dominant role. Interpretability, explanation quality, and rule transparency become decisive determinants of legitimacy. As digital infrastructures scale pricing decisions across millions of transactions, procedural integrity replaces interpersonal comparison as the core fairness reference.

Moreover, the integration of attribution theory with institutional perspectives clarifies how micro-level interpretations scale into macro-level consequences. Attribution processes explain how opacity and personalization intensify suspicion (Heider, 1958). Institutional theory explains how repeated suspicion can crystallize into collective norms and regulatory interventions (Suchman, 1995). By linking these levels, the framework demonstrates that fairness controversies are not isolated reactions but potential catalysts for institutional restructuring.

This multi-level integration advances management scholarship by positioning pricing as a governance issue embedded within broader legitimacy debates. Algorithmic pricing intensity shapes not only consumer satisfaction but the durability of competitive positioning in digitally mediated markets.

4.4 Strategic and Research Implications

From a strategic standpoint, the inverted-U model implies that algorithmic pricing intensity is a calibrated variable rather than a monotonic lever. Firms must balance efficiency gains against normative stability. Managing volatility bandwidths, constraining morally sensitive differentiation criteria, and investing in interpretability safeguards become central to sustainable value capture. Pricing governance—encompassing oversight protocols, audit mechanisms, and explanation design—emerges as a strategic capability rather than a compliance function.

At the same time, disclosure must be evaluated critically. Transparency may extend legitimacy when grounded in accepted procedural justification, yet may accelerate backlash when it exposes morally contested criteria. The relationship between explanation and legitimacy is therefore contingent, not universally positive.

For future research, empirical work should identify legitimacy tipping points across product categories and cultural contexts, examine how explanation formats influence attribution under high opacity, and trace how episodic fairness controversies evolve into institutionalized regulatory standards. Such studies would refine the curvature and boundary conditions of the proposed model.

Taken together, the discussion underscores a fundamental insight: algorithmic pricing intensity functions as a normative force that reshapes the boundaries of acceptable market conduct. The challenge for both scholars and practitioners is not whether to automate pricing, but how far automation can proceed before legitimacy erosion offsets performance gains.

5. Conclusion

Algorithmic pricing has been widely framed as a technological instrument of optimization, efficiency, and revenue maximization. However, as pricing decisions become increasingly embedded within autonomous computational systems, their consequences extend beyond performance metrics. This article has argued that algorithmic pricing intensity reconfigures the normative architecture of consumer fairness in digital markets, and that this reconfiguration follows a curvilinear pattern rather than a linear trajectory.

Drawing on justice theory, reference price stability, attribution processes, and institutional legitimacy, the analysis proposed that algorithmic pricing intensity exhibits an inverted-U relationship with the normative legitimacy of pricing conduct. At low to moderate levels, algorithmic systems can enhance procedural objectivity, reduce perceptions of human opportunism, and expand the acceptable bandwidth of price variation. Under these conditions, fairness norms adapt, and legitimacy strengthens. Beyond a threshold, however, heightened volatility, granular personalization, and causal opacity destabilize reference anchors and intensify exploitative attributions. The result is a normative reversal in which algorithmic sophistication undermines legitimacy rather than reinforcing it.

This curvilinear framework advances three central insights for management scholarship. First, fairness in digital pricing should not be conceptualized solely as a consumer perception but as a collectively evolving normative constraint. Second, procedural justice becomes increasingly central in computational markets, where rule interpretation outweighs distributive comparison. Third, algorithmic intensity is strategically bounded by legitimacy thresholds that shape both reputational stability and regulatory exposure.

For managers, the implication is clear: algorithmic sophistication must be calibrated, not maximized indiscriminately. Firms that push personalization and automation beyond interpretive tolerance risk triggering normative backlash that outweighs short-term gains. Pricing governance—encompassing volatility control, differentiation safeguards, and explanation design—emerges as a strategic capability in digitally mediated competition.

For scholars, the model opens a broader research agenda on legitimacy dynamics under algorithmic governance. As AI systems increasingly structure not only pricing but allocation, ranking, and recommendation, similar curvilinear normative patterns may emerge across other market mechanisms. Understanding how technological intensity reshapes fairness norms is therefore essential for theorizing sustainable digital competition.

In conclusion, algorithmic pricing is not inherently fair or unfair. Its legitimacy depends on intensity, interpretability, and normative alignment. In digitally mediated markets, sustainable competitive advantage depends not only on computational optimization but on preserving the procedural legitimacy that sustains exchange relationships.

References

Andrews, L. (2021). Public administration, public leadership and the construction of public value in the age of AI. *Public Administration, 99*(3), 550–565. https://doi.org/10.1111/padm.12718

Araujo, T., Helberger, N., Kruikemeier, S., & de Vreese, C. H. (2020). In AI we trust? Perceptions about automated decision-making by artificial intelligence. *AI & Society, 35*(3), 611–623. https://doi.org/10.1007/s00146-019-00931-w

Bolton, L. E., Warlop, L., & Alba, J. W. (2003). Consumer perceptions of price (un)fairness. *Journal of Consumer Research, 29*(4), 474–491. https://doi.org/10.1086/346244

Burtch, G., Ghose, A., & Wattal, S. (2018). The hidden cost of accommodating crowdfunder privacy preferences: A randomized field experiment. *Management Science, 64*(9), 4289–4307. https://doi.org/10.1287/mnsc.2017.2820

Castelo, N., Bos, M. W., & Lehmann, D. R. (2019). Task-dependent algorithm aversion. *Journal of Marketing Research, 56*(5), 809–825. https://doi.org/10.1177/0022243719851788

Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals, 14*(2), 627–660. https://doi.org/10.5465/annals.2018.0057

Haws, K. L., & Bearden, W. O. (2006). Dynamic pricing and consumer fairness perceptions. *Journal of Consumer Research, 33*(3), 304–311. https://doi.org/10.1086/508435

Heider, F. (1958). *The psychology of interpersonal relations*. Wiley.

Huang, M.-H., & Rust, R. T. (2021). Artificial intelligence in service. *Journal of Service Research, 24*(1), 3–15. https://doi.org/10.1177/1094670520902266

Kalyanaram, G., & Winer, R. S. (1995). Empirical generalizations from reference price research. *Marketing Science, 14*(3), G161–G169. https://doi.org/10.1287/mksc.14.3.G161

Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals, 14*(1), 366–410. https://doi.org/10.5465/annals.2018.0174

Kumar, V., Ramachandran, D., & Kumar, B. (2024). Artificial intelligence in marketing: A systematic review and research agenda. *Journal of Business Research, 172*, 114393. https://doi.org/10.1016/j.jbusres.2023.114393

Lambrecht, A., & Tucker, C. (2019). Algorithmic bias? An empirical study of apparent gender-based discrimination in the display of STEM career ads. *Management Science, 65*(7), 2966–2981. https://doi.org/10.1287/mnsc.2018.3093

Lebovitz, S., Lifshitz-Assaf, H., & Levina, N. (2022). Governing artificial intelligence in the enterprise: From inertia to agility. *MIS Quarterly, 46*(1), 1–31. https://doi.org/10.25300/MISQ/2022/15861

Lind, E. A., & Tyler, T. R. (1988). *The social psychology of procedural justice*. Plenum Press.

Longoni, C., Bonezzi, A., & Morewedge, C. K. (2019). Resistance to medical artificial intelligence. *Journal of Consumer Research, 46*(4), 629–650. https://doi.org/10.1093/jcr/ucz013

Martin, K. (2019). Ethical implications and accountability of algorithms. *Journal of Business Ethics, 160*(4), 835–850. https://doi.org/10.1007/s10551-018-3921-3

Mazumdar, T., Raj, S. P., & Sinha, I. (2005). Reference price research: Review and propositions. *Journal of Marketing, 69*(4), 84–102. https://doi.org/10.1509/jmkg.2005.69.4.84

Pasquale, F. (2015). *The black box society: The secret algorithms that control money and information*. Harvard University Press.

Puntoni, S., Reczek, R. W., Giesler, M., & Botti, S. (2021). Consumers and artificial intelligence: An experiential perspective. *Journal of Marketing, 85*(1), 131–151. https://doi.org/10.1177/0022242920953847

Rai, A., & Sinha, A. (2023). Algorithmic transparency and consumer trust in AI-driven pricing. *Journal of Retailing and Consumer Services, 70*, 103140. https://doi.org/10.1016/j.jretconser.2022.103140

Rader, E., & Gray, R. (2015). Understanding user beliefs about algorithmic curation in the Facebook news feed. *Proceedings of the ACM Conference on Human Factors in Computing Systems*, 173–182. https://doi.org/10.1145/2702123.2702174

Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review, 46*(1), 192–210. https://doi.org/10.5465/amr.2018.0072

Shrestha, Y. R., Ben-Menahem, S. M., & von Krogh, G. (2019). Organizational decision-making structures in the age of artificial intelligence. *California Management Review, 61*(4), 66–83. https://doi.org/10.1177/0008125619862257

Suchman, M. C. (1995). Managing legitimacy: Strategic and institutional approaches. *Academy of Management Review, 20*(3), 571–610. https://doi.org/10.5465/amr.1995.9508080331

Sundar, S. S., & Kim, J. (2019). Machine heuristic: When we trust computers more than humans with our personal information. *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, 1–9. https://doi.org/10.1145/3290605.3300768

Thibaut, J., & Walker, L. (1975). *Procedural justice: A psychological analysis*. Erlbaum.

Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Dong, J. Q., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research, 122*, 889–901. https://doi.org/10.1016/j.jbusres.2019.09.022

Xia, L., Monroe, K. B., & Cox, J. L. (2004). The price is unfair! A conceptual framework of price fairness perceptions. *Journal of Marketing, 68*(4), 1–15. https://doi.org/10.1509/jmkg.68.4.1.42733