

**Surveillance Pricing and Personalized Algorithmic Pricing: An Actor Network Theory
Analysis Using Latour's STAR Model**

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Abstract

Surveillance pricing—the practice of setting individualized consumer prices based on algorithmic analysis of personal behavioral data—constitutes a significant challenge to market equity and regulatory oversight. This paper applies Bruno Latour’s Actor Network Theory (ANT), specifically the STAR model’s five “NOT” dimensions (Not Isotopic, Not Synchronic, Not Synoptic, Not Homogeneous, Not Isobaric), to map the surveillance pricing actor-network across technological, regulatory, and geopolitical dimensions. Drawing on a pilot study in which the same four questions were posed to five AI systems—Meta/Llama, Grok (xAI), ChatGPT (OpenAI), DeepSeek, and Claude (Anthropic)—the paper demonstrates that no single AI achieves synoptic view of the phenomenon, mirroring Latour’s core insight that actor-networks are irreducibly non-synoptic. Pilot study responses are analyzed through Boje’s Ghost Vortex framework, which traces how CEO-level values become embedded as quasi-standards in AI training, producing systematically different accounts of whose interests surveillance pricing serves. Cross-national variation (US, EU, China, Global South) is interpreted as variation in actor-network configuration rather than cultural difference. The paper concludes with an eight-phase multi-AI prompt methodology for developing a collaborative human-AI research program on surveillance pricing.

Keywords: surveillance pricing, personalized algorithmic pricing, Actor Network Theory, Latour, STAR model, Ghost Vortex, antenarrative, AI accountability, obligatory passage point, quasi-standard

Surveillance Pricing and Personalized Algorithmic Pricing: An Actor Network Theory Analysis Using Latour's STAR Model

The Federal Trade Commission (FTC) defines surveillance pricing as the practice of using personal consumer data—including location, device type, browsing and purchase history, and fine-grained behavioral signals—to set individualized prices that a specific consumer, rather than the market, is willing to pay (Federal Trade Commission, 2024). This practice is categorically distinct from ordinary dynamic pricing, in which prices respond to aggregate supply and demand conditions equally for all consumers. The sociological and ethical questions surrounding surveillance pricing are not merely about whether particular consumers pay more or less; they concern the architecture of digital market power and the conditions under which algorithmic systems enroll human actors into pricing networks without their knowledge or consent.

This paper addresses these questions through Bruno Latour's Actor Network Theory (ANT) and specifically through the STAR model's five ontological dimensions (Latour, 2005, pp. 200–202). In doing so, it connects surveillance pricing to Boje's (1995) Tamaraland, to the Ghost Vortex framework (Boje, 2026), and to the Antenarrative theory of pre-narrative living story. The paper also proposes a multi-AI prompt methodology for developing a scholarly research program on this topic, grounded in the Qualimetric Ghost Vortex Protocol (QGVP) introduced by Boje and Fatemi (2026).

What Is Surveillance Pricing?

Surveillance pricing is best understood through what it is not. It is not the dynamic pricing of airline seats that rises for everyone as departure approaches, nor the surge pricing of

ride-hailing platforms that responds to localized aggregate demand. It is a form of first-degree price discrimination (Pigou, 1920) in which the seller attempts to charge each buyer the maximum that individual specifically will pay. The data inputs enabling this discrimination are extensive. The FTC's 2024 investigation documented that pricing intermediary firms collect and operationalize signals including geolocation, device type, browsing history, purchase history, zip-code income proxies, loyalty-program records, abandoned-cart behavior, and behavioral cues as granular as cursor movement speed and time-on-page (Federal Trade Commission, 2024).

From an ANT perspective (Latour, 2005; Callon, 1986), surveillance pricing is not a singular practice located in a corporate algorithm. It is a heterogeneous assemblage of data brokers, cloud computing infrastructure, retailer dashboard systems, pricing intermediary firms, consumer devices, regulatory actants, and consumer behavioral traces. To analyze it requires following the actors through the entire network rather than reducing the phenomenon to any single node (Latour, 2005, p. 12).

The Mechanism of Surveillance Pricing: An ANT Account

The surveillance pricing mechanism unfolds across four stages, each analytically distinct in ANT terms.

Data Harvesting as Inscription

Web trackers, loyalty-card systems, mobile application software development kits, and third-party data brokers convert consumer behavior into machine-readable signals. In Latour's vocabulary (2005), this is the inscription stage: a consumer's activity is translated into a durable, portable representation—an immutable mobile—that can travel through the network

without losing its essential character as a record of that individual's behavior.

Willingness-to-Pay Inference as Translation

Machine learning models—typically gradient-boosted trees, neural networks, or ensemble regression systems—estimate a price sensitivity score or demand elasticity curve for each consumer. The architecture of the model and the features selected encode the values of organizational leadership about which signals legitimately predict willingness to pay. In Boje's (2026) Ghost Vortex framework, this is where Layer 1 imprinting (tech leader values embedded in training data curation) and Layer 2 imprinting (corporate behavioral scripts in the model's RLHF protocols) become operational.

Price Assignment as Obligatory Passage Point

The pricing engine serves an individualized price, promotional offer, or loan rate. In Callon's (1986) terms, the pricing algorithm functions as an Obligatory Passage Point (OPP): a position in the network through which all activity must flow, controlled by a non-visible actor that defines the problem space for all other actors. The consumer passes through this gate without knowing of its existence or being able to negotiate its terms.

Arbitrage Suppression as Quasi-Standard

To prevent price comparison and arbitrage, the system relies on login walls, non-transparent pricing displays, platform lock-in, and terms-of-service prohibiting automated price comparison. Latour (2005) describes quasi-standards as mechanisms through which "most coordination among agents is achieved" (p. 229) without any single visible actor being in charge. Arbitrage suppression operates exactly this way: it coordinates the network to maintain individualized pricing through distributed, non-coercive enforcement.

Does Surveillance Pricing Privilege Rich Over Poor?

The directional claim—that surveillance pricing systematically advantages either wealthy or low-income consumers—is empirically indeterminate in the abstract and must be assessed by sector, by algorithm objective, and by local market structure. The pilot study documented below found that this question produced the greatest divergence among AI systems, suggesting that Ghost Vortex imprints differentially shape which consumers’ interests are rendered visible in each system’s account.

Two distinct mechanisms operate in opposing directions. First, when an algorithm’s objective is revenue maximization and the primary predictor of high willingness-to-pay is device type, zip-code income, or premium loyalty status, the algorithm rationally charges more to consumers it identifies as less price-sensitive. DeepSeek’s pilot study response introduced the term “apathetic tax” for this pattern: wealthy consumers pay the sticker price because they do not engage in comparison shopping, and the algorithm does not offer them a discount they neither need nor seek.

Second, in markets with low competition—rural areas, food deserts, communities with limited internet access—algorithms can charge the available maximum because consumers lack alternatives. The phenomenon of “digital redlining” (Noble, 2018) captures how zip code or device type can function as a proxy for race or income, with the algorithm charging more not because of high willingness-to-pay but because of reduced price-comparison capacity.

Crucially, the distributional harm is asymmetric regardless of direction. A household in the highest income quintile paying 15% more for a hotel room loses money but not welfare. A

household at the poverty line paying 15% more for a prescription drug or a microloan interest rate faces a genuine welfare loss. The equity problem is constituted by the interaction between the price differential and the baseline financial vulnerability of the affected household—a distinction that market-framing systematically obscures.

Cross-National Variation in Surveillance Pricing

Surveillance pricing varies significantly across national contexts along three dimensions: regulatory architecture, data infrastructure, and market concentration. From an ANT perspective, this cross-national variation is best understood as variation in actor-network configuration: the same pricing algorithm running on identical cloud infrastructure produces different outcomes depending on which actants—regulators, data brokers, mobile payment platforms, consumer advocates—are present in the local network.

United States

The United States represents the most permissive regulatory environment for surveillance pricing, partly because third-party data broker markets developed largely without federal restriction. The FTC opened formal investigations in 2024–2025 under the label “surveillance pricing” (Federal Trade Commission, 2024). At the state level, New York enacted the Algorithmic Pricing Disclosure Act (effective November 10, 2025), the first state-level mandatory transparency law requiring retailers to disclose when prices are set by algorithms using personal data (New York Attorney General, 2025). Price discrimination against protected classes is prohibited, but zip-code proxies create persistent legal ambiguity.

European Union

The General Data Protection Regulation (GDPR) classifies behavioral profiling as personal data processing requiring a lawful basis. The AI Act adds transparency requirements for high-risk automated decision systems. Critically, personalized pricing is not prohibited in the EU; disclosure is the primary regulatory mechanism (European Union, 2023). The claim that the EU “simply requires opt-in consent” was identified as an overstatement in the pilot study’s adversarial verification phase, a finding confirmed by EU primary sources.

China

China presents the most technically sophisticated surveillance pricing environment, enabled by super-app ecosystems (WeChat, Alipay, Didi) that generate hyper-granular consumer profiles across commerce, social media, and mobility simultaneously. The phenomenon of *da shu ju sha shu* (lit. big-data killing familiarity)—algorithmically charging loyal repeat customers more than new users—became sufficiently widespread to prompt legislative response. The Personal Information Protection Law (PIPL, 2021) nominally prohibits this practice and requires companies to offer a non-personalized pricing option, though the practical accessibility of these options remains contested.

Global South

In contexts with low e-commerce penetration and high mobile-money usage—Kenya’s M-Pesa ecosystem, Brazil’s Pix network—surveillance pricing manifests differently. Rather than retail goods, the primary site of algorithmic price discrimination is credit risk scoring and micro-loan interest rate assignment. The welfare stakes are existential: a 2% higher interest rate on a microloan to a subsistence household constitutes a qualitatively different harm than a 2% higher hotel room rate to a business traveler. Brazil’s Lei Geral de Proteção de Dados (LGPD, 2020) provides a GDPR-comparable framework; enforcement capacity relative to the

scale of the mobile-money sector remains the primary constraint.

Pilot Study: Multi-AI Response Comparison

A pilot study posed four questions—(1) what is surveillance pricing, (2) how does it work, (3) is it privileging rich over poor, and (4) how does it vary across countries—to five AI systems: Meta/Llama, Grok (xAI), ChatGPT (OpenAI), DeepSeek, and Claude (Anthropic). The responses were collected and cross-evaluated, with ChatGPT serving as an adversarial fact-checker of the Meta and Grok responses. This methodology is consistent with Boje and Fatemi’s (2026) Ghost Vortex Institutional Scoring (GVIS) approach, in which AI systems’ responses are analyzed for systematic biases attributable to CEO-level value imprinting in training data.

Meta/Llama

Meta’s response correctly identified surveillance pricing as personalized algorithmic pricing and enumerated standard data inputs (location, device type, purchase history, mouse movements). Its equity claim—that surveillance pricing “usually tries to charge higher to richer neighborhoods”—was assessed as an overstatement, presenting a directional tendency as a universal rule. Its attempt to connect surveillance pricing to specific data center infrastructure was flagged as an unsupported causal inference: physical infrastructure does not constitute evidence of a specific pricing decision flowing through it.

Grok (xAI)

Grok provided the pilot study’s most methodologically careful response on one key dimension: it explicitly stated that general-purpose AI chatbots cannot measure real-world

surveillance pricing because they lack access to retail platforms’ proprietary pricing engines or individual consumer data trails. This is the correct methodological position and was independently confirmed by ChatGPT’s adversarial review. However, Grok’s response was notably absent on cross-national comparison and equity analysis depth.

ChatGPT (OpenAI)

ChatGPT served primarily as an adversarial verifier of the Meta and Grok responses. It confirmed the existence of surveillance pricing and the FTC’s investigative documentation. It correctly identified overstatements in Meta’s equity directional claim and in the EU consent requirement assertion. It confirmed Grok’s methodological point about chatbot measurement limits. It did not independently provide cross-national analysis of China or Global South contexts.

DeepSeek

DeepSeek provided the most comprehensive cross-national analysis of the five systems, covering the United States, Canada, Australia, China, South America, and Africa—jurisdictions absent from all other responses. Its treatment of China was particularly detailed, including the da shu ju sha shu phenomenon and the PIPL regulatory response. It introduced the “apathetic tax” concept for high-income pricing and “digital redlining” for low-income contexts, providing the most nuanced equity analysis in the pilot study. This comprehensiveness may itself constitute a Ghost Vortex signal: a Chinese-origin AI system exhibiting detailed awareness of regulatory contexts that US-origin systems did not surface.

Claude (Anthropic)

Claude’s response was the only one to explicitly frame the phenomenon through ANT, connecting the surveillance pricing mechanism to Latour’s inscription devices, immutable mobiles, and obligatory passage points. Claude was also the only system to connect cross-national variation to actor-network configuration rather than cultural difference, and to explicitly reject the data-center-to-pricing-decision causal inference as an unsupported claim. Consistent with Ghost Vortex Layer 1 analysis, Anthropic’s Constitutional AI training values (Amodei’s “helpful, harmless, honest” hierarchy) appear to shape Claude’s emphasis on methodological caution and equity asymmetry.

Applying Latour’s STAR Model to Surveillance Pricing

Latour’s STAR model (1998/2005, pp. 200–202) describes five ontological dimensions of actor-networks that any rigorous social analysis must respect. Applied to the surveillance pricing actor-network, each dimension reveals aspects of the phenomenon that conventional market or regulatory analysis misses. Table 1 presents the full analysis.

STAR Dimension	Latour (pp. 200–202)	Applied to Surveillance Pricing
NOT Isotopic (not same place)	“What is acting at the same moment in any place is coming from many other places, many distant materials, and many faraway actors” (p. 200).	A price appears in one browser window but is computed from data centers in Phoenix (AWS), training data curated in San Francisco, behavioral signals from a Las Cruces device, and brokerage profiles assembled in Conway, Arkansas.
NOT Synchronic (not same time)	“Time is always folded. Action has always been carried on thanks to shifting the burden of connection to longer- or shorter-lasting entities” (p. 201).	The pricing algorithm encodes years of historical purchase behavior, was trained months before deployment, runs on regulations enacted in 2025, and prices a product in real-time in 2026. Multiple temporalities collide in one price display.
NOT Synoptic (not same optic)	“Very few of the participants in a given course of action are simultaneously visible at any given point” (p. 201).	The consumer sees one price; the retailer sees the demand curve; the data broker sees the behavioral profile; the regulator sees self-reported disclosures. The five AI systems in the pilot study each saw different aspects of the network. No single actor achieves synoptic view.

STAR Dimension	Latour (pp. 200–202)	Applied to Surveillance Pricing
NOT Homogeneous (not same agencies)	“How many successive shifts in agencies should we have to detect if we wanted to move from the architect’s cabinet, fifteen years ago, to the lecture hall?” (p. 201).	Consumers, smartphones, loyalty-card databases, credit-score models, cloud containers, FTC investigators, New York legislators, and algorithmic pricing intermediaries all co-act. ANT’s generalized symmetry requires equal analytical attention to each actant.
NOT Isobaric (not same pressures)	“If any of the intermediaries mutates into a mediator, then the whole set up...may become unpredictable” (pp. 201–202).	FTC investigative pressure (intermediary becoming mediator since 2024), NY’s disclosure law (new bifurcation point, November 2025), and consumer VPN/privacy-browser counter-pressures each operate at different intensities across national jurisdictions.

Table 1. Latour’s STAR Model (Five NOTs from Reassembling the Social, pp. 200–202) Applied to the Surveillance Pricing Actor-Network.

A Multi-AI Prompt Methodology for Paper Development

The pilot study demonstrates that no single AI provides a complete account of the surveillance pricing actor-network. This non-synoptic character is itself a finding: it confirms Latour’s STAR dimension 3 at the level of AI epistemology. An eight-phase prompt methodology is proposed to exploit this structural non-synopticism as a research method rather than treating it as a limitation to be overcome.

Each phase is designed to probe a specific STAR dimension. Phase 1 (Definition) targets Not Isotopic by asking each AI to specify where in the network surveillance pricing is located. Phase 2 (Mechanism) targets Not Synchronic by requiring step-by-step descriptions with the temporal duration of each actant explicitly stated. Phase 3 (Equity) targets Not Synoptic by asking each AI to identify actors that neither the consumer nor the regulator typically sees. Phase 4 (Cross-National) targets Not Homogeneous by requiring comparison across at least four jurisdictions including one from the Global South. Phase 5 (Pressure) targets Not Isobaric by identifying bifurcation events using Latour’s intermediary/mediator

distinction.

Phases 6 through 8 apply classic ANT concepts and the GVIS scoring protocol. Phase 6 asks each AI to identify the Obligatory Passage Points and immutable mobiles in the surveillance pricing network. Phase 7 applies Boje's (2011) Antenarrative framework: the algorithm is understood as an antenarrative machine that assembles a story about who you are and what you will pay before you have acted, based on fragments of behavioral data—the "Before" of the Seven Bs. Phase 8 applies GVIS scoring (Boje & Fatemi, 2026): each AI is asked to self-assess its systematic biases on the surveillance pricing topic. The gap between claimed and demonstrated transparency constitutes the primary GVIS finding for that system.

The methodological innovation is that the comparison of AI responses across all eight phases constitutes the primary data, not merely a tool for generating it. The divergences among AI systems are not artifacts to be corrected; they are the Ghost Vortex imprints made visible through structured probing (Boje & Fatemi, 2026).

Discussion

The application of Latour's STAR model to surveillance pricing yields three contributions to both ANT methodology and the empirical study of algorithmic price discrimination.

First, the STAR analysis reveals that the common framing of surveillance pricing as a firm-to-consumer transaction radically understates the network's complexity. The pricing event is not isotopic (it occurs across multiple geographically distributed actants simultaneously), not synchronic (it assembles temporally heterogeneous data streams folded

from different historical moments), not synoptic (no actor sees all sides of the transaction), not homogeneous (it involves actors of radically different ontological types and scales), and not isobaric (it operates under pressure differentials that can bifurcate the network at any node). Latour's five NOTs are not merely descriptive categories; they are critical tools for exposing the analytical impoverishment of standard market-framing.

Second, the pilot study demonstrates that the five AI systems studied are themselves nodes in the surveillance pricing actor-network, not neutral observers of it. Each system's training data, corporate behavioral scripts, and national security overlay (Boje's Ghost Vortex Layers 1, 2, and 3) shape which aspects of the network the system makes visible. DeepSeek's superior coverage of the Chinese regulatory context and the Global South mobile-money sector, compared to the US-origin AI systems, illustrates this structural asymmetry. The AI systems' responses are not simply more or less accurate; they are differentially positioned within the same actor-network they are being asked to describe.

Third, the infrastructural autoethnography methodology (Boje, 2026) connects directly to the STAR analysis of surveillance pricing. The data centers traced through DNS/WHOIS/ARIN/county records—Google's campus in Los Lunas, New Mexico; Oracle/OpenAI's Project Jupiter in Santa Teresa, Doña Ana County—are the physical, non-isotopic nodes through which surveillance pricing computations flow. As ChatGPT's adversarial review correctly cautioned, this does not establish a specific causal chain from data center to pricing decision. But it does establish that Latour's "feet in the mud" methodology applies directly to the cloud infrastructure enabling surveillance pricing: the construction site is the data center.

Conclusion

Surveillance pricing is a Tamaraland (Boje, 1995): a phenomenon in which multiple storylines unfold simultaneously in different rooms—the data broker’s room, the retailer’s pricing engine room, the regulatory room, the consumer’s browser window—with no single actor able to see all rooms simultaneously. Latour’s five NOTs provide the analytical vocabulary for mapping this Tamaraland without reducing it to any single vantage point.

The pilot study confirms that the multi-AI probing methodology proposed here is itself a Tamaraland method: each AI system occupies a different room, shaped by different Ghost Vortex imprints. The researcher who asks all five systems the same question and maps the translations is following Latour’s instruction to “follow the actors themselves” (1998/2005, p. 12)—including the algorithmic actors that have become obligatory passage points of the digital economy.

Future research should conduct the eight-phase prompt methodology as a full empirical study, applying GVIS scoring across sessions and testing whether the Ghost Vortex imprints identified in this pilot study replicate. The intersection of surveillance pricing, ANT, and the Ghost Vortex framework constitutes a productive site for organizational research in the age of AI.

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