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May 14, 2026

Joel Christie
Acting Secretary
Federal Trade Commission
Office of the Secretary
600 Pennsylvania Avenue, NW
Mail Stop H-144 (Annex F)

Re: Food Delivery Fees ANPRM (Project No. P267101)

The Future of Privacy Forum (FPF) welcomes the opportunity to submit comments in response to the Federal Trade Commission (FTC)'s Advanced Notice of Proposed Rulemaking (ANPRM) to address “unfair” or “deceptive” practices involving fees for online food retail and food delivery platforms.¹ FPF is a global non-profit organization dedicated to advancing principled and pragmatic data protection, AI, and digital governance practices in support of emerging technologies.

Specifically, the Commission requests information on the practice of “personalized pricing.” FPF recently published a report, ***The Price is Right: Responsible Uses of Personal Data in Pricing***, which was developed in consultation with leading retailers and other businesses.² The report explores how retailers use consumer and merchant data to inform the prices they offer customers, how lawmakers and enforcers in the U.S. are regulating personalized pricing, and some current best practices for the responsible use of personal data in pricing. The report's findings are summarized below, and a copy of the report is attached to this comment.

Retailers' pricing strategies take into account a wide variety of data, including information about supply and demand, production costs, competitor prices, and other market forces.³ As such, prices can vary significantly over time and across consumers as conditions change—even when based strictly on market forces and not individual consumers' personal information. For

¹ Federal Trade Commission, *Advance notice of proposed rulemaking; request for public comment: Rule on Unfair or Deceptive Fees in Online Food Delivery Services* (Apr. 16, 2026), <https://www.federalregister.gov/documents/2026/04/16/2026-07473/rule-on-unfair-or-deceptive-fees-in-online-food-delivery-services>.

² Jameson Spivack, *The Price is Right: Responsible Uses of Personal Data in Pricing*, Future of Privacy Forum (Apr. 2026), <https://fpf.org/wp-content/uploads/2026/04/FPF-Data-Driven-Pricing-The-Price-is-Right-Report.pdf>.

³ Jameson Spivack, *Data-Driven Pricing: Key Technologies, Business Practices, and Policy Implications*, Future of Privacy Forum (Jul. 14, 2025), <https://fpf.org/resource/data-driven-pricing-key-technologies-business-practices-and-policy-implications/>.

example, ride hailing apps engage in “surge pricing” during busy times and hotels fluctuate prices by season, both reflecting changes in supply and demand.⁴

However, as consumer data becomes more widely accessible, machine learning algorithms more advanced, and online retail more ubiquitous, retailers increasingly have the ability to adjust prices based on individual consumer data, in real-time or near-real-time. Personalized pricing builds on, and expands, a long history of retailers tailoring prices to customers based on individual characteristics or inferences—from special offers for students or military personnel, to negotiating in the marketplace.⁵ Modern practices like targeted discounts and “bona fide” loyalty programs, which are common and generally viewed as beneficial, are often based on and supported by retailers’ access to large amounts of personal consumer data. For example, a retailer could offer a discount to a first-time visitor to their website, or to a lapsed customer who hasn’t made a purchase in a while.

The following non-exhaustive table shows some of the most common sources and types of data used to power personalized pricing.⁶

DATA SOURCES	DATA TYPES
<ul style="list-style-type: none"> ● First-party data (collected by retailer) ● Partner companies ● Data brokers ● Financial institutions ● Online advertising ecosystems ● Mobile and other connected devices ● Social media ● Government agencies ● Open datasets ● Third-party app developers 	<ul style="list-style-type: none"> ● Online transaction behavior (e.g., purchases, cart additions, micro-interactions like clicks) ● Other online behavior (e.g., browsing history, marketing email interactions) ● Geolocation ● Demographics (e.g., age, family status) ● Social connections ● Time of day ● Device data (e.g., model type, IP address, browser used)

⁴ Cvent Europe Ltd, *Hotel Dynamic Pricing: The Complete Guide for Hoteliers*, Hospitality Net (Nov. 7, 2025), <https://www.hospitalitynet.org/report/4129687/hotel-dynamic-pricing-the-complete-guide-for-hoteliers>. See also Jessica Phillips, *How Uber’s Dynamic Pricing Model Works*, Uber Blog (Jan. 21, 2019), <https://www.uber.com/en-GB/blog/uber-dynamic-pricing/>.

⁵ The practice of “price discrimination,” or varying prices across customers for the same product, has likely always played a role in commerce. For a detailed explanation of how price discrimination works, as well as its legal implications in the U.S., see Hal R. Varian, *Price Discrimination*, CREST Working Paper No. 87-26 (Jan. 1987), <https://backend.production.deepblue-documents.lib.umich.edu/server/api/core/bitstreams/b6daf384-21a8-4fbc-ad9f-43821f2ada95/content>.

⁶ *Algorithmic Pricing and Competition: Discussion Paper*, Government of Canada Competition Bureau (Jun. 10, 2025), <https://competitionbureau.canada.ca/en/how-we-foster-competition/education-and-outreach/publications/algorithmic-pricing-and-competition-discussion-paper>.

- Language

While in many cases personalized pricing is intended to attract or retain customers, retailers' expanding access to consumer and market data, and advanced pricing algorithms, provides them with insights that could be used to personalize prices in ways that the average consumer might find unexpected or exploitative. For example, retailers could individualize prices based on inferences about consumers' wealth, life circumstances, or willingness to pay for a product, drawn from information such as spending habits, ZIP code, or the device used to make a purchase.⁷

Generally speaking, consumers, enforcers, and lawmakers are in agreement that in most cases, personalized pricing should be clearly disclosed or consented to, and that retailers failing to do so risk violating long-standing consumer protection laws.⁸ However, beyond the expectation that personalized pricing be disclosed, there is little consensus or explicit guidance around which uses of personal data in pricing are fair and legitimate. The extent to which personalized pricing benefits retailers and consumers, as well as more fundamental questions about the fairness of varying prices based on personal data, remain open to debate.

In the absence of more formal rules, modern retailers should proactively demonstrate and communicate how and why their uses of personal data in pricing are beneficial to consumers or, at the very least, provide assurances they are fundamentally fair. In general, they should avoid uses of consumer data that are unexpected, might reflect or perpetuate societal biases, or could be considered unfair or deceptive. The following recommendations, developed with feedback from retailers, highlight best practices for building trustworthy pricing practices involving personal data.

⁷ Rafi Mohammed, *How Retailers Use Personalized Prices to Test What You're Willing to Pay*, Harvard Business Review (Oct. 20, 2017), <https://hbr.org/2017/10/how-retailers-use-personalized-prices-to-test-what-youre-willing-to-pay>. See also Jennifer Valentino-DeVries, Jeremy SingerVine, & Ashkan Soltani, *Websites Vary Prices, Deals Based on Users' Information*, The Wall Street Journal (Dec. 24, 2012), <https://www.wsj.com/articles/SB10001424127887323777204578189391813881534>. See also Dana Mattioli, *On Orbitz, Mac Users Steered to Pricier Hotels*, The Wall Street Journal (Aug. 23, 2012), <https://www.wsj.com/articles/SB10001424052702304458604577488822667325882>.

⁸ For studies of consumer sentiment, see *Gartner Marketing Survey Finds 68% of Consumers Report They Feel Taken Advantage of When Brands Use Dynamic Pricing*, Gartner Newsroom (Dec. 16, 2024), <https://www.gartner.com/en/newsroom/press-releases/2024-12-16-gartner-marketing-survey-finds-68-percent-of-consumers-report-they-feel-taken-advantage-of-when-brands-use-dynamic-pricing>. For the California Attorney General's investigation of "surveillance pricing" in the grocery, hotel, and retail sectors, see *On Data Privacy Day, Attorney General Bonta Focuses on Surveillance Pricing, Compliance with California Consumer Privacy Act*, State of California Department of Justice (Jan. 27, 2026), <https://oag.ca.gov/news/press-releases/data-privacy-day-attorney-general-bonta-focuses-surveillance-pricing-compliance>. For a discussion of emerging state legislation addressing "surveillance pricing," see Austin Jenkins, *States Move to Curb AI-Driven 'Surveillance Pricing'*, Pluribus News (Jan. 23, 2026), <https://pluribusnews.com/news-and-events/states-move-to-curb-ai-driven-surveillance-pricing/>.

1. Map and track the collection and use of all data that informs consumer pricing over time, including data sources and provenance.
2. Rigorously test all relevant datasets and pricing algorithms for bias.
3. Establish clear internal policies around what data types and uses of data are permitted for informing consumer prices, based on an analysis of fairness, context, and consumer expectations.
4. Provide clear disclosures to consumers about how data informs pricing, and how personal data may inform personalized offers.
5. Ensure that personalized discounts exist in relation to real “baseline” prices.
6. Implement stronger safeguards around data-driven pricing for essential products.
7. Ensure alignment on data use policies when partnering with pricing algorithm vendors.

Attached to this comment you will find FPF’s recent report, ***The Price is Right: Responsible Uses of Personal Data in Pricing***, which provides more detailed information and serves as a foundation for retailers to further develop personalized pricing best practices, based on an analysis of consumer expectations, context, and fairness.

FPF appreciates the opportunity to comment on these issues, and the FTC’s ongoing efforts to address the privacy and fairness questions raised by personalized pricing. We welcome any further opportunity to provide resources or information to assist in this vital effort. If you have any questions regarding these comments, or the attached report, please contact Jameson Spivack at jspivack@fpf.org (cc: info@fpf.org).

Sincerely,

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The Price is Right

Responsible Uses of Personal Data in Pricing

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EXECUTIVE SUMMARY

The way prices are set is changing: more accessible data, sophisticated algorithms, and ubiquitous online shopping have given retailers the ability to automatically tailor offers to customers in real-time or near-real-time based on increasing amounts of data about markets and consumers. A number of pricing strategies involving personal data, market data, and advanced machine learning—what this resource refers to collectively as “**data-driven pricing**”—have recently become common marketing practice. While data-driven pricing is often deployed to attract, retain, or reward customers, it can also provide retailers with insights that could be used to individualize prices in ways that average consumers might find unexpected or unfair, or that cause unintended disparities across groups. For these reasons, data-driven pricing has become the subject of increasing scrutiny from civil society, lawmakers, and enforcers in the United States.

This resource provides an overview of how data is used to inform pricing; contextualizes data-driven pricing in existing U.S. law, enforcement activity, and emerging legislation; and recommends a number of best practices for guiding retail and e-commerce platforms in using data responsibly when it affects pricing. **These practical recommendations, developed in consultation with companies working to build trustworthy pricing practices, are aligned with how leading organizations have built robust, responsible AI Governance programs based on frameworks like National Institute of Standards and Technology (NIST)’s AI Risk Management Framework (AI RMF).**

Recommendations include:

- › Map and track the collection and use of all data that informs consumer pricing over time, including data sources and provenance.
- › Rigorously test all relevant datasets and pricing algorithms for bias.
- › Establish clear internal policies around what data types and uses of data are permitted for informing consumer prices, based on an analysis of fairness, context, and consumer expectations.
- › Provide clear disclosures to consumers about how data informs pricing, and how personal data may inform personalized offers.
- › Ensure that personalized discounts exist in relation to real “baseline” prices.
- › Implement stronger safeguards around data-driven pricing for essential products.
- › Ensure alignment on data use policies when partnering with pricing algorithm vendors.

I. How Data Informs Pricing

In retail and commerce, pricing strategies are [informed by a wide variety of data](#), including information about supply and demand, production costs across different geographic regions, competitor prices, and other market forces.¹ As such, prices can vary over time and across consumers as conditions change. For example, hotel and airline prices fluctuate based on seasonality, rooms or seats available, fuel prices, and expected demand.² Ride hailing apps and delivery services, similarly, have “surge pricing” or “busy fees” when demand is high.³ Retailers have also long conducted market analysis, surveys, and experiments to assess supply and demand to inform the prices they offer.

In recent years, however, advancements in modern machine learning and AI systems have allowed commercial platforms and retailers to apply sophisticated pricing engines that can adjust pricing in real-time or near-real-time, based on far greater quantities of data about markets or consumer behavior. As public awareness of automated pricing grows, questions inevitably arise about the extent to which pricing may be responsive to data from or about individual consumers. This section explores how retailers use both personal and non-personal data to set prices, how the role of data and machine learning in pricing is evolving, and the challenges this raises for retailers trying to maintain responsible data practices.

1. Retailers use a broad range of non-personal data to inform prices, a process that is increasingly automated and optimized using machine learning.

It is common for retailers to change the price of a particular product—sometimes in real-time or near-real-time—based on an analysis of [market conditions](#) or [temporal and spatial factors](#), a practice known as “dynamic pricing” (see Figure 1).⁴ In the former, retailers adjust their prices in response to shifts in supply or demand, or as competitors’ prices change. Retailers may also alter their prices based on [geographic location](#) or [point in time](#) (such as time of day, day of the week, or season) to account for general economic trends across time and place.⁵ For example, a retailer may adjust prices based on information about the weather or cost of living in a particular area, or historical data about consumer demand for certain products in a [given season](#).⁶

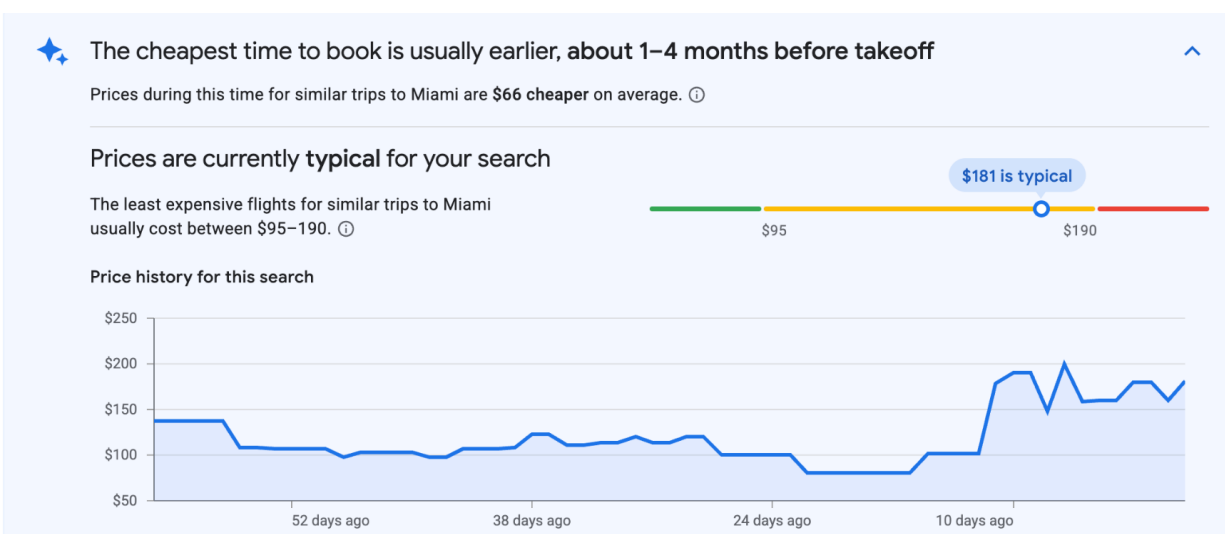


Figure 1. A common example of dynamic pricing can be found in commercial airline flight prices, which often fluctuate over time based on demand and other factors. Google Flights provides historical trend data for consumers to compare rates for airline tickets over time. Screenshot taken Feb. 11, 2026.

In many cases, dynamic pricing is adjusted automatically in response to changing conditions. Common examples of dynamic pricing include surge pricing in [ride hailing apps](#), [hotel room rental rates](#) that fluctuate by season, and [airline tickets](#) that increase in price closer to the flight. However, in other cases, such as [happy hour](#) specials, matinee showings for movie theaters, markdowns for grocery items reaching their expiration dates, and “market price” listings in restaurants, they are adjusted “manually” and less frequently.

2. Retailers have access to expanding sources of personal data, which informs a wide range of personalized discounts strategies.

Retailers have [long used personal data](#) in some capacity to inform prices.⁷ The practice of “[price discrimination](#),” or charging different consumers different prices for the same product based on observed or inferred characteristics, has a long history in commerce.⁸ Providing special discounts for students, seniors, or friends and family, for instance, has been a popular practice for decades. Haggling, bartering, and negotiating over price is also common, whether in traditional marketplaces or modern settings like car dealerships. In fact, the concept of uniform prices for goods and services across customers is a relatively modern phenomenon, purportedly pioneered by American Quakers in the mid-to-late 1800s.⁹

In recent decades, however, more [personalized and dynamic pricing](#) models have grown as data has become more accessible, algorithms more sophisticated, and online retail more ubiquitous.¹⁰ Many commercial platforms and retailers now have the ability to deploy sophisticated pricing systems that can adjust prices in real-time or near-real-time based on large amounts of data about markets or consumers. Pricing strategies like [targeted discounts](#), [dynamic pricing](#), and “bona fide” [loyalty programs](#) have since become common marketing practices.¹¹

A large [ecosystem](#) of entities that collect, analyze, and transfer data makes modern pricing strategies possible.¹² The data that informs prices can be drawn from a range of first-party and third-party sources, and decisions about how this data should impact prices can be made by the retailer, a third-party pricing tool, or a marketplace or advertising platform. While retailers usually collect data directly from customers as they browse their online store, retailers may also have access to a significant amount of data from [other sources](#) via tracking pixels, cookies, software development kits (SDKs), and other methods of tracking users across sessions, applications, and devices.¹³

The following non-exhaustive table shows some of the most common [sources and types of data](#) used in data-driven pricing. Depending on the retailer, data can be first-party or third-party, and can be either directly-observed data or information inferred about consumers.¹⁴

DATA SOURCES	DATA TYPES
<ul style="list-style-type: none"> › First-party data (collected by the retailer) › Partner companies › Data brokers › Financial institutions › Online advertising ecosystems › Mobile and other connected devices › Social media › Government agencies › Open datasets › Third-party app developers 	<ul style="list-style-type: none"> › Online transaction behavior (e.g., purchases, browsing, cart additions and abandonment, micro-interactions like clicks or cursor hovering) › Other online behavior (e.g., browsing history, marketing email interactions) › Geolocation › Demographics (e.g., age, family status) › Social connections › Time of day › Device type (e.g., model type, IP address, browser used) › Language

Based on consumers' observed or inferred personal data, retailers are able to offer prices or special deals [calculated specifically for individual customers](#).¹⁵ Most commonly, pricing is personalized in the form of targeted discounts or loyalty programs. In the case of targeted discounts, retailers offer promotions based on a customer's behavioral or demographic information, such as providing coupons to consumers after their first visit to a retail website, or sending direct-mail coupons to residents within a geographic area. Retailers may place consumers into [market segments](#) with others who share similar characteristics; these can be broad, such as "teachers" or "seniors," or can be more targeted and based on granular personal data (e.g., "new parents who make over \$80,000 a year and buy groceries online at least once a month").

In the case of loyalty programs, customers sign up to receive rewards, discounts, or other incentives from a specific company, typically in exchange for repeat business or additional data sharing. These programs are often [tiered](#), providing different benefits corresponding to a customer's level of spending activity, length of time in the program, or fee to participate. Examples of common loyalty programs include [airline frequent flyer mile programs](#), hotel rewards programs, retail [membership programs](#), and [credit card rewards programs](#).¹⁶

In many cases, personalized pricing is a way for retailers to attract or retain customers. For example, a retailer may offer a discount to a lapsed customer who hasn't made a purchase in a while, provide a special offer for a similar product based on their recent purchases, or waive a fee or offer a discount on future purchases in response to complaints. Retailers may also use more granular data, such as the amount of time spent lingering on a website without making a purchase, or items left in a cart, to infer a customer's level of interest and entice them with special offers.

3. The use of personal data in pricing can be expected and legitimate, but presents challenges in terms of explainability, transparency, and fairness.

In some cases, the use of personal data in the broader context of pricing can be both expected and legitimate. For example, a device's geolocation can be used to reflect actual geographic differences in prices. Personal data is also typically used to offer personalized discounts, such as providing coupons to consumers after their first visit to a retail website, or a direct-mail coupon targeted to residents within a geographic area. These kinds of practices are now typically fully automated, and the result is often beneficial for both parties: retailers are more likely to make a sale, and consumers benefit from discounted prices.

At the same time, given their expanding access to data and advanced machine learning models, retailers face increasing pressure to explain their pricing strategies and demonstrate that their uses of data are fair. While many of these strategies are beneficial to consumers, retailers also have access to personal consumer data that would allow them to personalize pricing in ways that consumers might find exploitative. For example, [if they wanted](#), retailers could leverage existing data sources, as described above, to individualize prices based on consumers' inferred wealth or life circumstances.¹⁷ They could also infer the maximum price a customer is [willing to pay](#) and charge them that amount, based on information such as spending habits, [ZIP code](#), or the [device](#) used to make the purchase.¹⁸ Distinguishing between legitimate and illegitimate uses of data is a major challenge for consumers, who are typically at an informational disadvantage with respect to how their data is used.¹⁹

[Consumers](#), [enforcers](#), and [lawmakers](#) are generally in agreement on the key point that in most cases, displaying an individualized price tailored to a specific consumer based on that consumer's personal data should be clearly [disclosed](#) or consented to, and otherwise can risk violating long-standing consumer protection laws—including protections against unexpected secondary uses of information.²⁰ What's considered fair or expected by consumers can be nuanced and depend on the specific context

of the consumer interaction. For example, direct mail marketing using first-party data is a well-established practice, as is offering promotional discounts to first-time visitors or customers who leave items in their online shopping carts without making a purchase. These kinds of practices have become routine, and in many cases might be expected or welcomed. At the same time, a retailer could leverage the same type of data—products viewed—to infer information about the consumer that is less expected, such as a health condition, and offer discounts on that basis. In such cases, the practice may [strike people as unfair](#).²¹

4. Almost all modern pricing is, to some extent, “algorithmic.”

In a general sense, “algorithmic” merely refers to a [structured decision-making process](#) that generates an outcome based on input data.²² As such, many pricing strategies are *algorithmic*, in that they provide an output (price) based on an automated [analysis](#) of consumer and market data.²³ What’s new about modern [algorithmic pricing](#) strategies, however, is the ability to automatically adjust prices in real-time or near-real-time based on large quantities of data, in order to optimize sales.²⁴ For example, many retailers employ [pricing engines](#) to set and manage prices across products and customers, accounting for supply and demand, competitor prices, geographic differences, special offers, and loyalty programs, among other things.²⁵ In many cases, pricing algorithms operate autonomously, with minimal or no human oversight. However, some retailers—particularly small and medium enterprises—change prices “manually” on a less-frequent basis, though still based on an analysis of market data.

II. Legal Landscape and Recent Legislative Trends

In the United States, issues related to the pricing of consumer goods and services are primarily governed by consumer protection, competition, and, to a growing extent, privacy and data protection laws. In recent years, data-driven pricing has also become a major legislative priority in the U.S., with lawmakers introducing over 60 bills a year in both 2025 and 2026.

1. Legal and Enforcement Landscape in the U.S.

In the U.S., federal and state consumer protection and competition laws provide enforcers broad discretion to enforce against practices they deem harmful or misleading, potentially including certain data-driven pricing practices. Section 5 of the [Federal Trade Commission \(FTC\) Act](#), for example, prohibits “[unfair or deceptive](#) acts or practices [“UDAP”] in or affecting commerce.”²⁶ Though the FTC has historically been hesitant to bring cases under its “unfairness” authority, it has [clarified](#) that it applies to practices that “unreasonably create[] or take[] advantage of an obstacle to the free exercise of consumer decisionmaking”—which [some argue](#) should apply to non-disclosed personalized pricing.²⁷ In 2024, the FTC began a significant [6\(b\) investigation](#) into “surveillance pricing” practices, which sought information about the various types of personal data retailers can use to set prices, and the ecosystem of actors facilitating individual price targeting.²⁸ While new FTC leadership in 2025 [cancelled](#) a planned public comment period, likely signaling the end of the 6(b) study,²⁹ state enforcers have since explicitly prioritized the issue, as discussed below.

Additionally, the FTC has issued [regulations on deceptive pricing](#), which provide guidance on avoiding practices like offering discounts from a “fictitious” baseline price, as well as a rule banning “[junk fees](#)” and bait-and-switch pricing.³⁰ In the financial sector, the Consumer Financial Protection Bureau (CFPB) enforces the [Consumer Financial Protection Act \(CFPA\)](#), and has released [supervisory guidance](#) clarifying that entities engage in unlawful “abusive conduct” when consequential terms about transactions—

including pricing or costs—aren't conveyed clearly to consumers, interfering with their ability to understand relevant terms or conditions.³¹ Other sectors, such as the [telecommunications](#) and [healthcare](#) industries, have their own regulations around how organizations can set and display prices.³²

The FTC, along with the Department of Justice (DOJ) and state enforcers, also has the authority to enforce federal competition and antitrust laws, including taking actions against entities facilitating price-fixing through the use of algorithms. For example, in 2025, the DOJ and eight state attorneys general (AGs) sued a property management software provider, alleging that the company engaged in “algorithmic coordination” by aligning rental prices among competing rental companies based on non-public, competitively-sensitive data.³³ Every state has its own consumer protection law that largely mirrors the FTC Act’s “UDAP” prohibition, enforced by state AGs. Most also have [price gouging laws](#), which prohibit charging exorbitant prices in certain circumstances such as natural disasters, and may require limits on automated price adjustments.³⁴

A. Consumer Privacy Laws

At least 19 states now have comprehensive privacy and data protection laws in effect that create relevant substantive requirements for organizations that process personal data, including in commercial settings that affect pricing. Specifically, provisions regarding data minimization, purpose limitation, and automated decision-making may provide enforcers a legal hook for scrutinizing the use of personal data or algorithms in setting prices. Nearly all state privacy laws contain some form of [data minimization requirement](#), which generally prohibit covered entities from collecting, using, or retaining more personal data than is necessary to accomplish an identified, lawful purpose. Many comprehensive consumer privacy laws also contain a “purpose limitation” principle, which limits the ways in which entities may use data collected for a specific purpose for additional unrelated, incompatible, or unexpected secondary purposes.³⁵

Maryland and California may differ in important ways from other state privacy laws in how they approach data minimization and purpose limitation. While the majority of state laws permit data collection and processing so long as the purpose is disclosed, the Maryland Online Data Privacy Act [provides](#) that controllers must “limit the collection of personal data to what is **reasonably necessary and proportionate** to provide or maintain a specific product or service **requested by the consumer** to whom the data pertains” (emphases added).³⁶ Meanwhile, the [California Consumer Privacy Act \(CCPA\)](#)’s [regulations](#) require that the “purpose(s) for which personal information is collected or processed shall be consistent with the **reasonable expectations** of the consumer,” and that collection and processing “shall be **reasonably necessary and proportionate** to achieve” a disclosed purpose (emphases added).³⁷ In January 2026, California AG Rob Bonta began an [investigative sweep](#) of businesses in the retail, grocery, and hotel sectors to determine if any are allegedly engaged in “surveillance pricing,” or using personal consumer data to set targeted, individualized prices.³⁸ According to AG Bonta, “surveillance pricing” may constitute a violation of the [CCPA](#)’s purpose limitation principle if the use of consumers’ personal data for pricing purposes is not consistent with their reasonable expectations.

Some consumer privacy and related laws contain requirements regarding the use of automated profiling technologies that are used to make significant or consequential decisions involving housing, healthcare, insurance, and other similar services. California’s [automated decision making technology \(ADMT\) regulations](#) require businesses, when using ADMT for significant decisions, to provide consumers notice before collecting or using personal data for the purpose of ADMT, allow consumers to opt out of ADMT, and respond to consumer requests to access information about how ADMT was used.³⁹ In practice, businesses may be subject to these obligations if they engage in automated, personalized pricing in the context of housing, education, or enumerated critical sectors.

Many of the comprehensive privacy protections in the U.S. have analogues in the European Union’s General Data Protection Regulation (GDPR) and other global data protection frameworks. Specifically, the GDPR includes baseline requirements related to fairness (Article 5), transparency (Art. 13-14), and the right to not be subject to [solely automated decision-making](#) (Art. 22) when it produces “legal or similarly significant effects.”⁴⁰ Although many uses of personal data in consumer retail pricing are likely to be considered “solely automated,” the threshold of “legal or similarly significant effects” typically applies only in high-stakes contexts, such as housing, healthcare, insurance premium pricing, or eligibility of government benefits.⁴¹ Its application to consumer personalized retail pricing has been debated but not resolved. In addition, the modernization of the EU’s [Consumer Rights Directive \(2019/2161\)](#) requires that retailers inform consumers when a price has been personalized through automated decision-making (ADM).⁴²

B. Algorithmic Pricing Laws

As of March 2026, states have enacted four laws specific to data-driven pricing: New York’s [Algorithmic Pricing Disclosure Act](#),⁴³ which requires companies to provide a specific disclosure to consumers when engaging in “personalized algorithmic pricing”; [New York S 7882](#),⁴⁴ which prohibits residential property owners coordinating prices through an “algorithmic device,” among other things; [California SB 325](#),⁴⁵ which amends the state’s antitrust law to prohibit using or distributing “common pricing algorithms” for colluding on rental prices; and [Connecticut HB 8002](#),⁴⁶ a broader housing bill that prohibits setting rental or occupancy rates with algorithmic pricing based on nonpublic competitor data.

The New York Algorithmic Pricing Disclosure Act—which [survived](#) a legal challenge by the [National Retail Federation](#) on First Amendment grounds—has been the subject of recent enforcement scrutiny.⁴⁷ The law requires companies to provide a disclosure to consumers when engaging in “personalized algorithmic pricing,” which is broadly defined to include “dynamic pricing set by an algorithm that uses personal data” (see Figure 2 below). In November 2025, New York AG Letitia James issued a [consumer alert](#) encouraging New Yorkers to report suspected violations.⁴⁸ More recently, following a [public interest research study](#), AG James sent an investigation letter to Instacart, [requesting more information](#) about the company’s use of consumer data and algorithms to set prices and discounts.⁴⁹

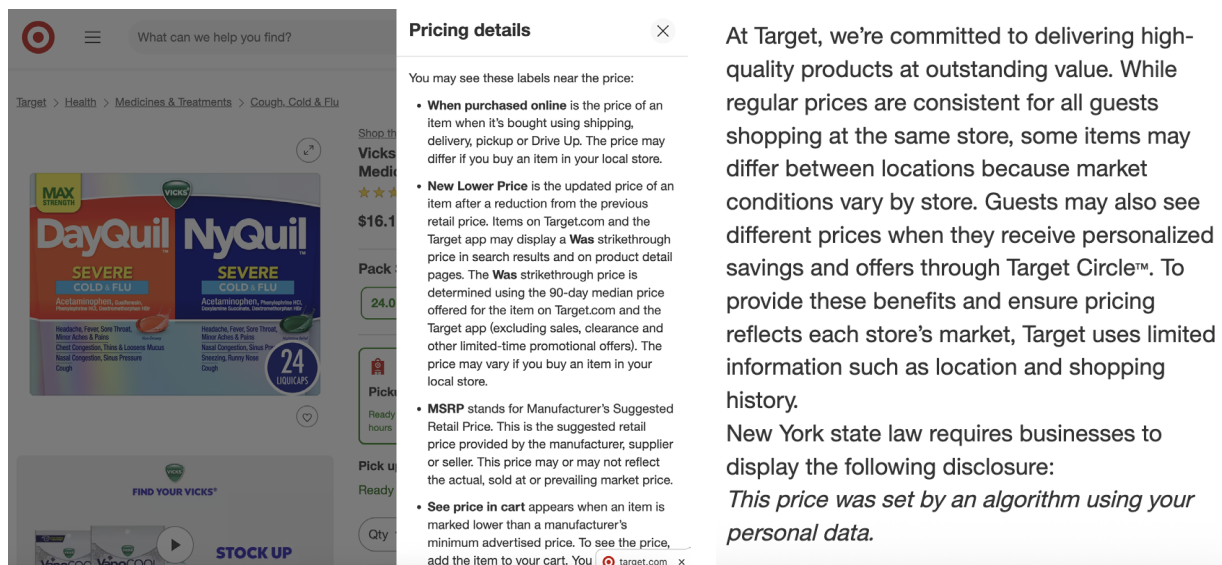


Figure 2. Products on Target’s website include an “info” icon next to the listed price, which triggers a slide-out menu with more pricing information, including legal disclosures required under the New York Algorithmic Pricing Disclosure Act. Screenshot taken Feb. 11, 2026.

C. U.S. Legislative Trends

As of March 2026, state and federal lawmakers have introduced over 70 bills in 2026 addressing a range of data-driven pricing practices.⁵⁰ Many proposed bills mirror New York’s Algorithmic Pricing Disclosure Act, mandating specific disclosures for personalized and/or algorithmic pricing, while others seek to generally ban “surveillance pricing” practices, particularly in essential areas such as food retail stores. In 2026, compared to previous years, a greater proportion of bills now seek to restrict “surveillance pricing” in retail overall, as contrasted with earlier focuses on housing and food retail.

Given the complexities involved in how personal and non-personal data are used in pricing, and the fact that most modern pricing can be considered “algorithmic,” lawmakers face real challenges in navigating a lack of consensus around which business practices should be considered acceptable versus unacceptable, particularly when the outcome depends on nuances of consumer expectations or relationships. As such, bills vary in how they scope increasingly nuanced exemptions for a wide variety of common practices, such as loyalty programs, legitimate cost differences in providing products across geographic areas, discounts with publicly-disclosed eligibility criteria, and commonly-understood social groupings like seniors and teachers.

III. Recommendations for Responsible Data-Driven Pricing

In order to maintain user trust, modern retailers should proactively demonstrate and communicate that their uses of data—both personal and non-personal—are legitimate, thoughtfully executed, and fundamentally fair. In general, retailers should avoid uses of consumer data that are unexpected, might reflect or perpetuate societal biases, or could be considered unfair or deceptive. When certain exceptions arise, retailers must be able to rely on clear internal policies, and to explain their pricing decisions to consumers, enforcers, and the public.

The following recommendations, developed in consultation with companies working to build trustworthy pricing practices, are intended as a guide for retail and e-commerce platforms to use data responsibly when it affects pricing.

1. *Map and track the collection and use of all data that informs consumer pricing over time, including data sources and provenance.*

In line with existing data governance approaches, retailers should develop [data maps](#) and track [data provenance](#) to better understand the source and lineage of the personal data they possess.⁵¹ In particular, retailers should be able to identify all the potential and actual data that is used in setting prices, which helps ensure data is handled in ways consistent with its intended purpose, based on the retailer’s policies around permitted uses in pricing decisions (see below). For example, by tracking data provenance, retailers can filter out data that violates their policies before it is added to a pricing engine. Mapping data also helps retailers conduct or comply with any audits or investigations of their practices, as they will be able to produce records of data used to set prices and its origin.

Data-driven pricing programs should be managed through a retailer’s data governance or AI governance process, which may be informed by widely-used frameworks such as the National Institute of Standards and Technology (NIST)’s [AI Risk Management Framework](#) (AI RMF) or the [ISO/IEC 42001](#) standard on AI management systems.⁵² Practitioners responsible for managing data-driven pricing should document any and all relevant data sources, data types, data maps, organizational policies, risk and impact assessments, algorithm training methodologies and outcomes, disclosure texts, and bias testing results around pricing decisions. Documenting this information is helpful not only for external investigations, but also as a method of establishing internal accountability.

2. Rigorously test all relevant datasets and pricing algorithms for unintended bias.

Retailers should, to the extent possible, evaluate the training data, algorithms, and fine-tuning data involved in pricing decisions to identify and mitigate risks of unfair bias or unlawful discrimination.⁵³ When implementing third-party pricing algorithms, retailers should seek appropriate transparency or contractual assurances from developers regarding bias testing and risk mitigation. While excluding protected traits from input data is a common practice to prevent direct discrimination, the exclusion of input data does not guarantee equitable outcomes.⁵⁴ Retailers should also assess their pricing strategies for unintended discriminatory effects, and be able to demonstrate that any pricing disparities that could disadvantage consumers based on a protected characteristic are the result of legitimate business interests, such as higher production or distribution costs.

In general, the rigor of bias testing and the depth of demographic analysis should be proportional to the potential impact on the consumer and the sensitivity of the product category. For example, pricing for essential goods or high-value services may warrant more intensive auditing, whereas retailers of general consumer goods may focus on broader outcome testing and high-level trend analysis. Documenting the methodologies and outcomes involved in the AI lifecycle will help retailers audit and justify their practices as part of a robust accountability framework. Retailers can integrate bias testing and mitigation procedures into their existing AI governance programs, drawing guidance from established standards like the NIST AI RMF or the ISO/IEC 42001.

3. Establish clear internal policies around what data types and uses of data are permitted for informing consumer prices, based on an analysis of fairness, context, and consumer expectations.

Retailers should establish clear internal policies for what data, or uses of data, are “always permitted,” “sometimes permitted,” or “always off limits” in pricing. Policies should be informed by a retailer’s data protection impact assessments, updated on a continuous basis if pricing algorithms or datasets change, and enforced by internal technical and organizational controls. Regulatory [guidance](#), emerging [enforcement activities](#), and [studies](#) of [consumer sentiment](#) can serve as helpful guideposts when making decisions about what pricing practices might be considered unfair or deceptive.⁵⁵ The “[reasonable consumer](#)” standard can also serve as a helpful guidepost, centering consumers’ expectations in evaluations of fairness.⁵⁶

4. Provide clear disclosures to consumers about how data informs pricing, and how personal data may inform personalized offers.

Where feasible, retailers should provide effective notices in multiple locations, including just-in-time or [layered](#) notices at the point of sale, disclosing when and how data is used to inform pricing or special offers.⁵⁷ These policies should also be published externally, as possible, to allow for ongoing transparency. Personalized discounts should be disclosed clearly—for example, with [strikethrough pricing](#) or individualized discount codes—to denote that a consumer is receiving a special offer in relation to a baseline price.⁵⁸ To the extent possible, retailers should also be able to provide contextual insight into how and why the personalized offer has been made; for instance, an explanation that a discount code is a “thank you” for making a recent purchase, or as part of a customer’s loyalty program. In the case of marketplaces and third-party advertisements, retailers will need to work with their data partners to determine who is responsible for providing disclosures: the entity setting the price, or the one displaying it.⁵⁹

Sometimes, retailers use personal data as a proxy for market conditions or legitimate, non-individualized pricing distinctions. For example, retailers in the transportation sector may use a consumer’s geolocation to set fares, but the price is based on more general market factors like supply, demand, or the cost of providing a product or service. In these cases, retailers should be clear that personal data is informing price only to the extent that it reflects broader market conditions, rather than personalization unique to the individual.

In some cases, such as mobile applications with limited design space, it will be necessary to put more detailed information about pricing in terms of service rather than at the point of sale, to avoid overwhelming consumers with information. For dynamic pricing, which may lack a universal baseline price, retailers can still provide transparency by providing details about how different factors impact a given price, or how prices have changed over time. For example, ride hailing apps can explain that prices increased due to higher demand or lower driver availability, and airline ticket websites can show how a price compares to historical prices. Overall, more transparency into pricing decisions leads to greater [consumer trust](#) in the retailer.⁶⁰

5. Ensure that personalized discounts exist in relation to real “baseline” prices.

Personalized discounts should be offered to consumers in relation to a “bona fide” baseline price, meaning one that has been recently offered to the public in good faith, during the regular course of business, for a reasonable amount of time. Offering a discount from a “fictitious” baseline price—such as an inflated price, or one the retailer never intended to offer—is considered a form of deceptive pricing according to the FTC’s [Guides Against Deceptive Pricing](#).⁶¹ This principle holds true for dynamic pricing: even in the absence of a universal price across customers, discounts should be made in relation to an original price that would be offered to an individual based on general market factors like supply, demand, or cost. Additionally, offering to waive fees or provide discounts as part of customer service, such as in response to customer complaints, is also a common and acceptable practice.

6. Implement stronger safeguards around data-driven pricing for essential products.

Pricing has greater economic impact in the context of essential services, such as housing, food, healthcare, and education, and should be subject to tighter controls. Retailers engaging in dynamic pricing in these sectors may have a greater responsibility to offer transparency into their practices, and to set reasonable parameters to prevent price gouging or instability, particularly in times of crisis or security threats. For example, retailers can set a reasonable cap on exorbitant price increases for products in an area affected by natural disaster. They can also institute automatic triggers for human review when a pricing algorithm increases above a certain price threshold, or more than a certain number of times, in a given time period. Additionally, retailers should implement escalation and remediation procedures with human oversight in the event of adverse impacts in high-risk contexts.

7. Ensure alignment on data use policies when partnering with pricing algorithm vendors.

In many cases, retailers [partner](#) with third-party pricing algorithm vendors, rather than developing the tool in-house.⁶² When doing so, retailers should require contractual controls around what data is used to inform prices and secondary uses of data, in line with the retailer’s own policies. Retailers should also require vendors to provide information about what data is used to set prices—without violating trade secret or intellectual property protections—in order to provide an adequate level of transparency to their customers. In markets like rental housing, retailers should avoid sharing any of their non-public, competitively-sensitive data with algorithm vendors, to avoid any potential [collusion](#) or [anticompetitive practices](#).⁶³

Appendix: U.S. Legislation Relating to Data-Driven Pricing, 2026

U.S. state and federal lawmakers introduced over 60 data-driven pricing bills in 2026, and over 70 in 2026. Most legislation focuses on one of three key elements: whether **algorithms** are used to set prices, whether consumers' **personal data** is used to set individualized prices, and whether data-driven pricing is being implemented in particularly sensitive **contexts**, such as rental housing or food retail. Generally, legislation takes one of four approaches, though some bills combine different elements:

- 1. New York-style disclosure requirements:** The first law specific to data-driven pricing enacted in the U.S. was New York S 3008C, which requires those engaged in “personalized algorithmic pricing” to include a clear and conspicuous disclosure stating “THIS PRICE WAS SET BY AN ALGORITHM USING YOUR PERSONAL DATA.” While some other bills require this same language verbatim, others are less prescriptive in terms of specific language to be used in the disclosure. Pricing practices commonly carved out in this style of legislation include insurers and financial institutions already regulated by other laws, as well as certain pricing that is part of a consumer’s subscription-based agreement with an entity.
- 2. General “surveillance pricing” prohibitions:** The broadest, and most common, of data-driven pricing legislation models involves a full prohibition on “surveillance pricing” or setting individualized prices based on “surveillance data.” While definitions of “surveillance pricing” vary, they generally apply to the act of setting customized prices for specific consumers based in whole or in part on their personal data. These bills usually exempt practices such as generally-available discounts and loyalty programs, personalized discounts, cost-based price differentials, and regulated entities like insurers or financial institutions. Some bills contain other unique elements, such as prohibitions on the use of minors’ data to set personalized prices in *all* cases (e.g., the enumerated exceptions don’t apply), prohibitions on the use of “surveillance data” to set wages, or prohibitions on the use of protected class data to set prices.
- 3. Food retail “surveillance pricing” prohibitions:** Given that food is an essential good, some lawmakers seek to prohibit the use of “surveillance,” algorithmic, or dynamic pricing in food retail establishments such as grocery stores. Some bills also seek to prohibit the use of electronic shelf labels in physical food retail stores. Common exceptions include personalized discounts, cost-based price differentials, loyalty programs, and insurers and financial institutions.
- 4. Housing “algorithmic collusion” prohibitions:** Lawmakers have sought to prohibit landlords and rental property managers from agreeing to use a common pricing algorithm trained with non-public, competitively-sensitive data to set housing rental prices, occupancy levels, or other lease terms. Three of the four existing data-driven pricing laws—New York S 7882, California SB 325, and Connecticut HB 8002—fall under this category. These bills are intended to address concerns that housing rental operators may, intentionally or not, engage in collusive price-fixing by agreeing to rely on a pricing algorithm that uses shared, non-public data. In a few cases, lawmakers have sought to ban “algorithmic collusion” in retail markets more generally, beyond housing.

The following table includes 2026 data-driven pricing legislation as of March 20, 2026.⁶⁴

Legislative approach	Bills
New York-style disclosure requirements	IL HB 4717 , UT SB 177 , CT SB 4 , IL HB 4248 , IL HB 4544 , IL HB 4717 , IL HB 5323 , MD HB 1479 , NE LB 1006 , UT SB 177
General “surveillance pricing” prohibitions	AZ HB 2489 , CA AB 2564 , CO HB 26-1210 , FL SB 1746/HB1499 , HI SB 2036 , HI HB 2136 , IL SB 2255 , IL SB 3657 , IL HB 4985 , IA HF 2469 , KY HB 33 , LA SB 362/HB 471 , MD HB 148 , MD SB 889 , MA HB 5612 , MN HF 3794/SF 4233 , MN HF 4131 , NJ S 3612/A 4085 , NJ S 4685 , NM SB 223 , NY S 8623/A 9349 , PA HB 1942 , PA SB 1205 (dynamic pricing prohibition for “essentials”), RI SB 2428 (surveillance and dynamic pricing prohibition), RI HB 7849 , TN HB 1468/SB 1807 , UT SB 293 , VT S 207 , VA HB 121 , VA SB 615 , WA SB 6312 , US S 3387 , US HR 4640
Food retail “surveillance pricing” prohibitions	GA HB 1439 , HI HB 2458 , MD SB 387 , MN HF 3408 , IA SF 2278 (disclosure), MD SB 387/HB 895 , MN HF 3408/SF 4199 , NJ S 3732 , NJ A 4523/S 3717 , NY A 3437 (dynamic pricing prohibition), NY S 8616/A 9396 , OK HB 3959 (disclosure), TN SB 1998/HB 2052 , WA HB 2481 , US HR 4966 , US S 3892
Housing “algorithmic collusion” prohibitions	AZ HB 2490 , GA HB 1520 , HI HB 2611 , MD HB 434 , MI SB 794 , NH HB 1612 , NJ S 451 , RI SB 2266 , RI HB 7129 , RI HB 7764 , TN SB 1990 , TN HB 2234/SB 1990 , VA SB 585 , VA SB 1252 , US S 6124
Other	IL SB 3027 (AI and pricing in hospitals), NE LB 771 (grants Governor discretion over dynamic pricing during emergencies), NY A 3103 (surge pricing prohibition), NY A 4427 (prohibition on insurance discrimination based on external consumer data), OH HB 665 (general prohibition on pricing algorithms trained with nonpublic data)

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- 48 *Consumer Alert: Attorney General James Warns New Yorkers About Algorithmic Pricing as New Law Takes Effect*, Office of the New York State Attorney General (Nov. 5, 2025), <https://ag.ny.gov/press-release/2025/attorney-general-james-warns-new-yorkers-about-algorithmic-pricing-new-law-takes>. AG James also authored an op-ed calling for even stronger limits on algorithmic pricing, suggesting that her office is prioritizing data-driven pricing in both enforcement and policy advocacy capacities. See Letitia James, *Commentary: New York must set stronger limits on algorithmic pricing*, Times Union (Jan. 16, 2026), <https://www.timesunion.com/opinion/article/algorithmic-pricing-new-york-21286819.php>.

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