

When AI Disclosure Backfires: The Economic Consequences of Labeling AI-Generated Review Summaries

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Policy Background

Policymakers across jurisdictions are **tightening transparency and accountability requirements** for **AI-generated content** in consumer-facing contexts:

US

FTC Consumer Reviews Rule

16 CFR Part 465

Targets fake or false consumer reviews and testimonials, including deceptive AI-enabled practices.

Not yet a general AI labeling mandate

Effective Oct 2024

CN

China AI Labeling

CAC Labeling Measures

Mandates explicit and implicit **labeling** of AI-generated synthetic content for covered network information service providers.

Effective Sep 2025

EU

EU AI Act

Regulation 2024/1689


Article 50 establishes transparency obligations for AI-generated or AI-manipulated content, including **marking** and detectability requirements.

Effective Aug 2026

While intended to preserve trust, these mandates raise an underexplored concern: **the potential unintended economic consequences of AI disclosure for digital platforms.**

Research Motivation

Review Summaries in E-commerce Platform



amazon prime

Stanley Quencher H2.0 FlowState Stainless Steel Vacuum Insulated Tumbler with Lid and Straw for Water, Iced Tea or Coffee

Visit the STANLEY Store

4.6 ★★★★★ 65,903 ratings | Search this page

Amazon's Choice in Tumblers & Water Glasses by STANLEY

10K+ bought in past month

\$35⁰⁰

prime One-Day FREE Returns

Get \$150 off instantly: Pay \$0.00 upon approval for Prime Visa.

May be available at a lower price from other sellers, potentially without free Prime shipping.

Style: 30 oz


14 oz 20 oz 30 oz 40 oz 64 oz

AI-generated from the text of customer reviews


Customers like the insulation, color, quality and size of the drinking cup. For example, they mention it keeps ice cold for a long time, it stands out well and that it's heavy duty. Some appreciate the size, saying it fits perfectly in their cup holders. That said, opinions are mixed on value.

✓ Insulation ✓ Quality ✓ Color ✓ Size Value — Condition

AI Labeling & Both Positive and Negative



CARMAX



★★★★☆ 4.3 out of 5 51 customer reviews

The 2012 Jeep Liberty is a car that has been well-received by customers. Customers like the car's design, the car's handling, and the car's performance. Customers also like the storage capacity and fuel efficiency.

No Labeling & Positive-Only

Research Questions

1.

How does the introduction of **review summaries** affect consumer shopping decisions across the purchase funnel?

- Consideration (e.g., dealer appointment)
- Conversion (e.g., purchase)

2.

To what extent does **source labeling** in **review summaries** influence consumer behavior?

- None
- AI attribution (e.g., “AI-Generated”)
- Human attribution (e.g., “Human Editor-Generated”)

3.

How do **content framing** (balanced vs. positive-only) and **source labeling** in **review summaries** jointly affect consumer decisions?

Experiment Context

We collaborated with a leading **automotive e-commerce platform** in Asia to conduct a **large-scale randomized field experiment**.



High Financial Stakes

Average vehicle price ~\$62,000.
Consumers scrutinize every information cue, including **source labels** of review summary.



Multi-Stage Decision Funnel

Consumers go through [product detail page] → [dealer consultation] → [purchase].
Clear separation of **consideration** and **conversion** stages.



High Information Asymmetry

This makes consumers highly **dependent on review summaries** to evaluate products.

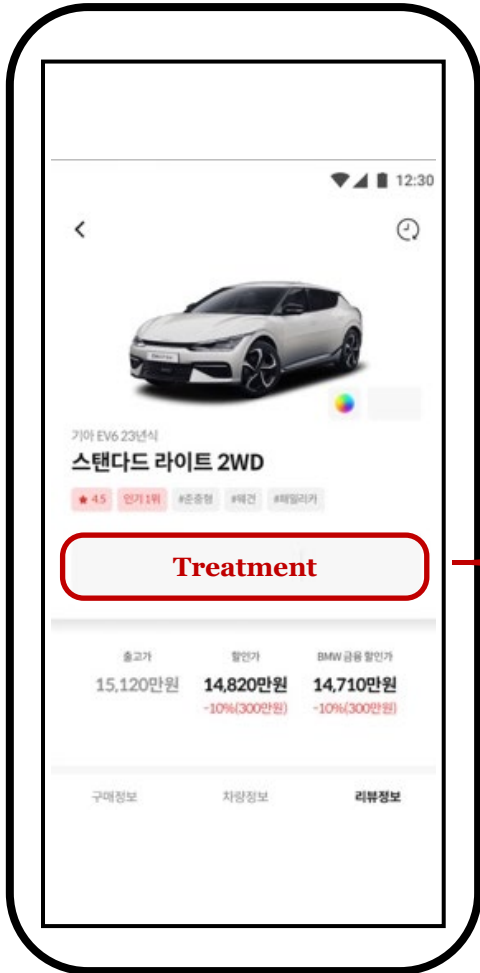
152,634
unique users

9 months
experiment period (Nov 2024 – Aug 2025)

7 conditions
2×3 factorial design + control

Field Experiment Design

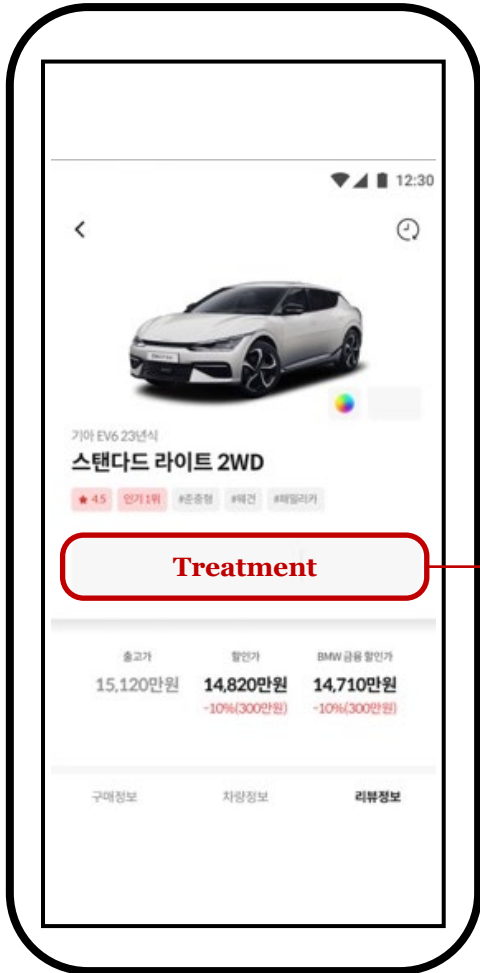
Product Page



Group	Condition	Source Labeling	Content Framing	Example
C	Control	No Review Summary		Carvana
G1	Treatment	None	Both Positive and Negative	Apple (App Store)
G2	Treatment	Human ("Human Editor-Generated")	Both Positive and Negative	
G3	Treatment	AI ("AI-Generated")	Both Positive and Negative	Amazon
G4	Treatment	None	Positive Only	CarMax
G5	Treatment	Human ("Human Editor-Generated")	Positive Only	
G6	Treatment	AI ("AI-Generated")	Positive Only	Newegg

Field Experiment Design

Product Page



Group	Source Labeling	Content Framing
G3	AI	Both Positive and Negative
<p>AI-Generated Review Summary</p> <ul style="list-style-type: none">Strengths: The vehicle offers spacious interiors and comfortable rides, making it great for families. Its design provides more room and steady comfort even on long trips.Weaknesses: The vehicle has high purchase and maintenance costs, reducing affordability. Its large size makes driving and parking difficult in city areas.		

Data

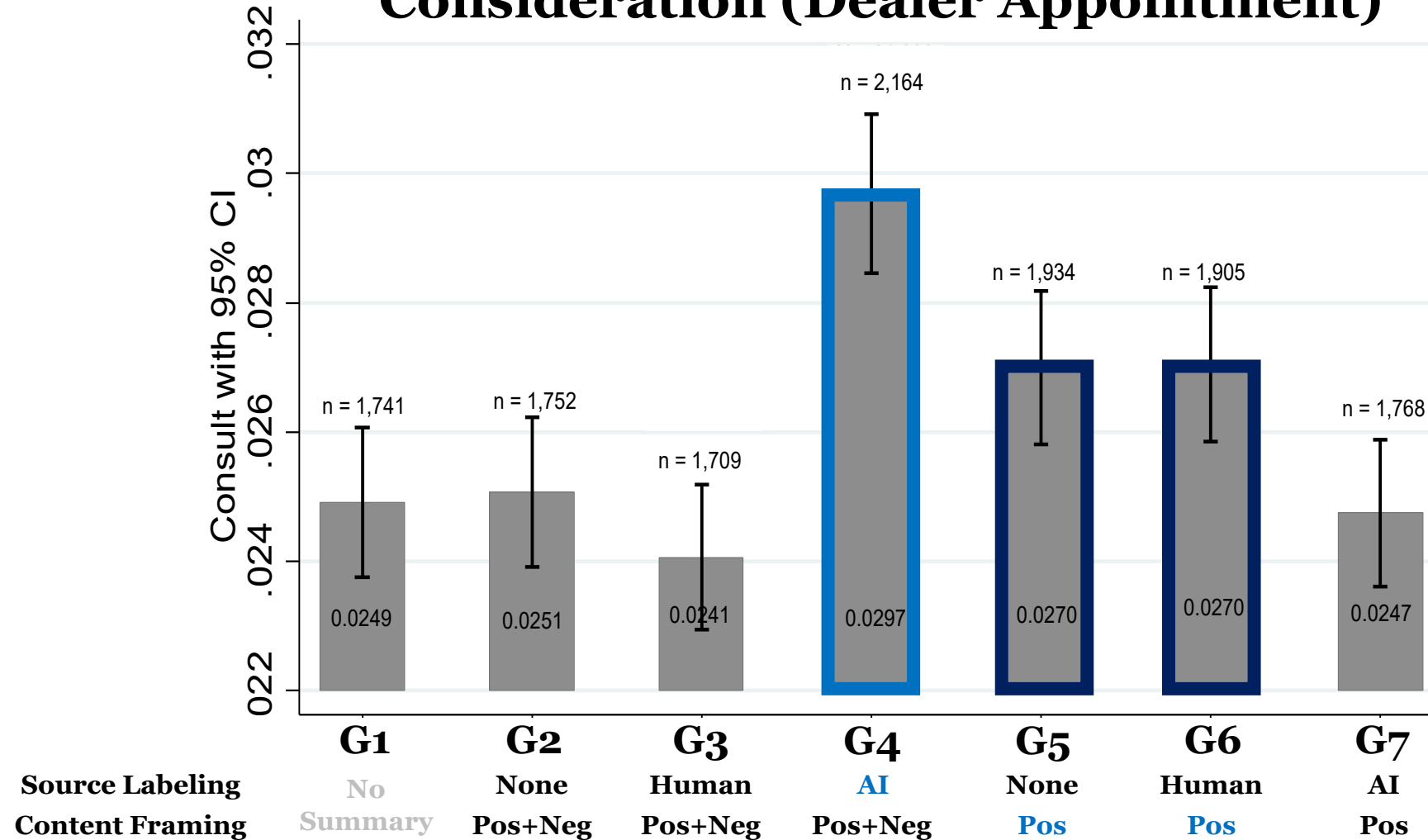
- **Nov 20, 2024 ~ Aug 30, 2025**
- **152,634 individuals**

(1) randomized field experiment + (2) individual shopping click stream + (3) individual transaction

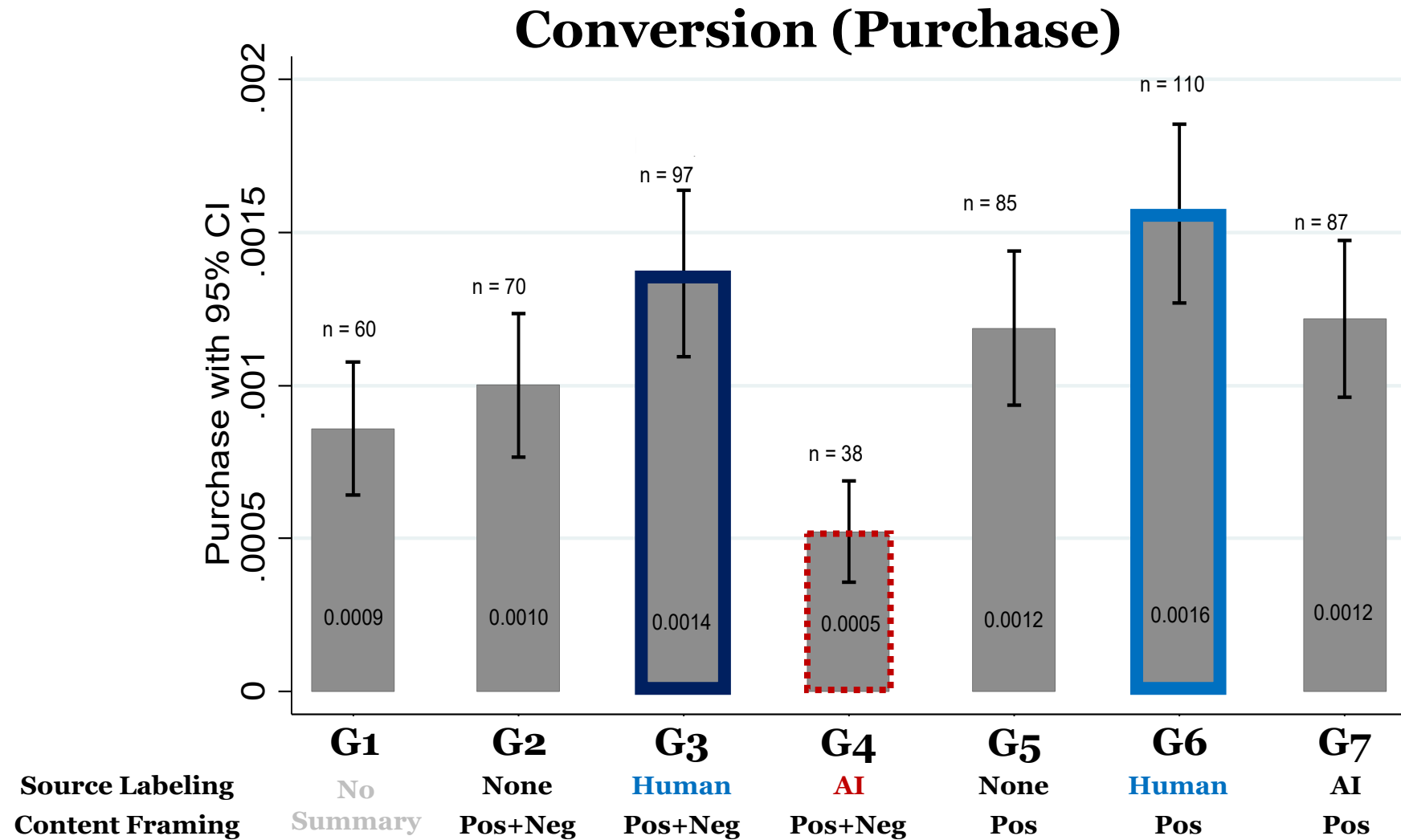
Category	Variable	Description	Mean	Min	Max
Dependent Variables	<i>Dealer Appointment</i>	A binary variable indicating whether a consumer (i) requested consultation for a car (j)	0.026	0	1
	<i>Purchase</i>	A binary variable indicating whether a consumer (i) purchased a car (j)	0.001	0	1
Control Variables	<i>Review Valence</i>	Average valence score of consumer reviews for a car (j) when a consumer (i) visited product page.	4.380	1	5
	<i>Review Volume</i>	The number of consumer reviews of a car (j) when a consumer (i) visited product page.	63.520	0	509
	<i>Price</i>	Fixed price of a car (j) (USD)	62,135.2	7,969.231	451,292.3
	<i>Brand</i>	A categorical variable of car (j) brand	12.435	0	34
	<i>Historical Browsing</i>	The number of cars searched by a consumer (i) prior to 6 months of experiment date (Nov 20, 2024)	3.643	0	73
	<i>Historical Consult Frequency</i>	The number of consult requests made by a consumer (i) prior to 6 months of experiment date (Nov 20, 2024)	0.014	0	4
	<i>Historical Average Price</i>	Average price of cars searched by a consumer (i) prior to 6 months of experiment date (Nov 20, 2024)	64,222.57	9,384.615	267,692.3

Model-Free Analysis: Effects on Dealer Appointment

Consideration (Dealer Appointment)

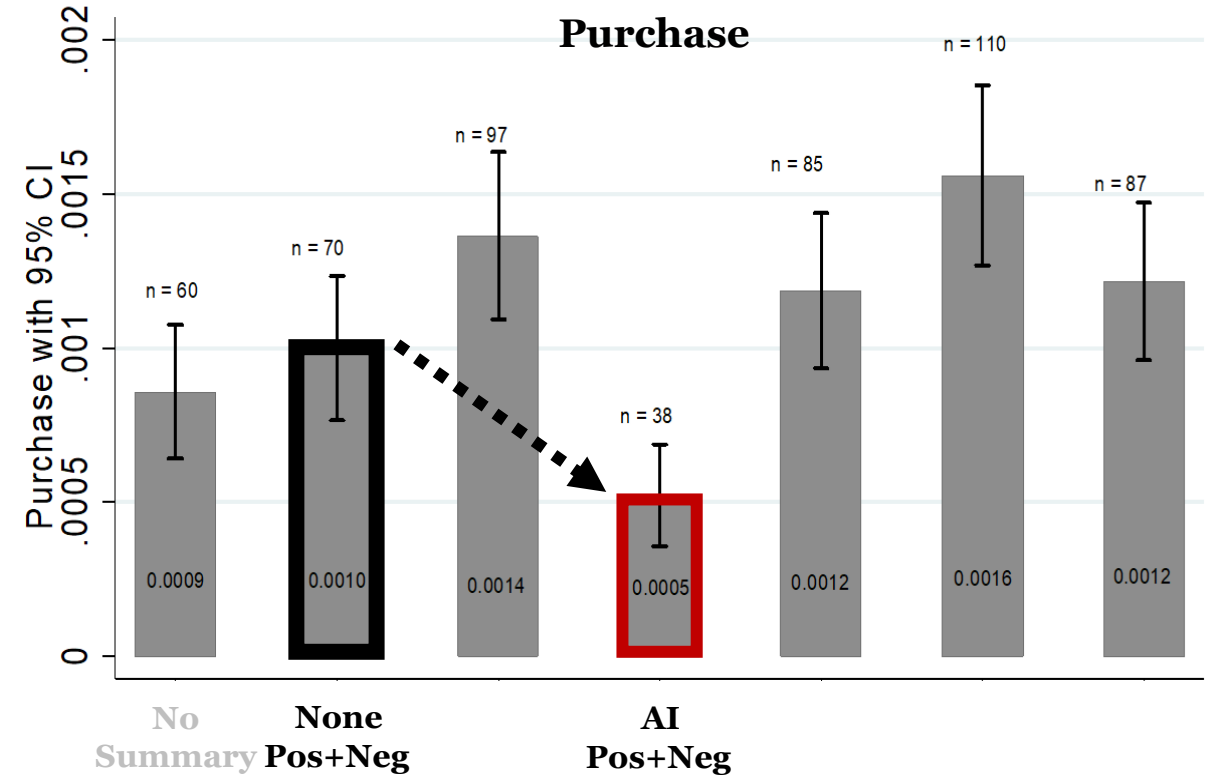
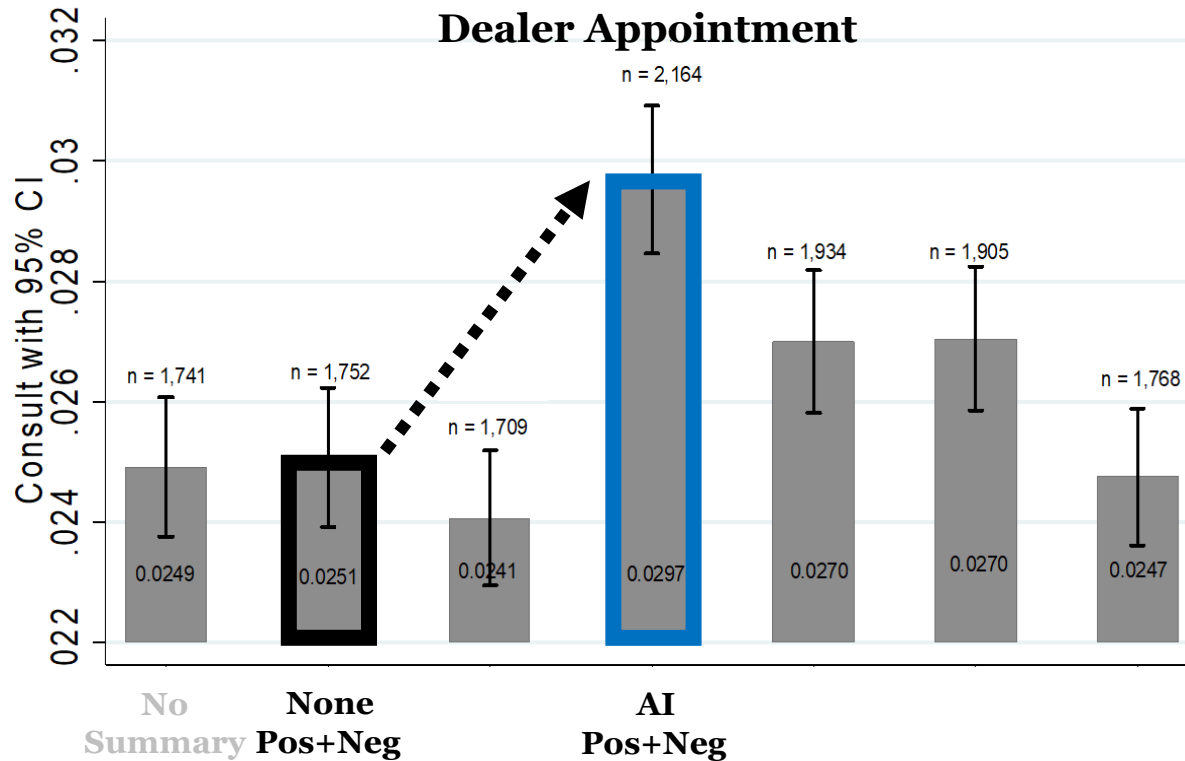


Model-Free Analysis: Effects on Purchase



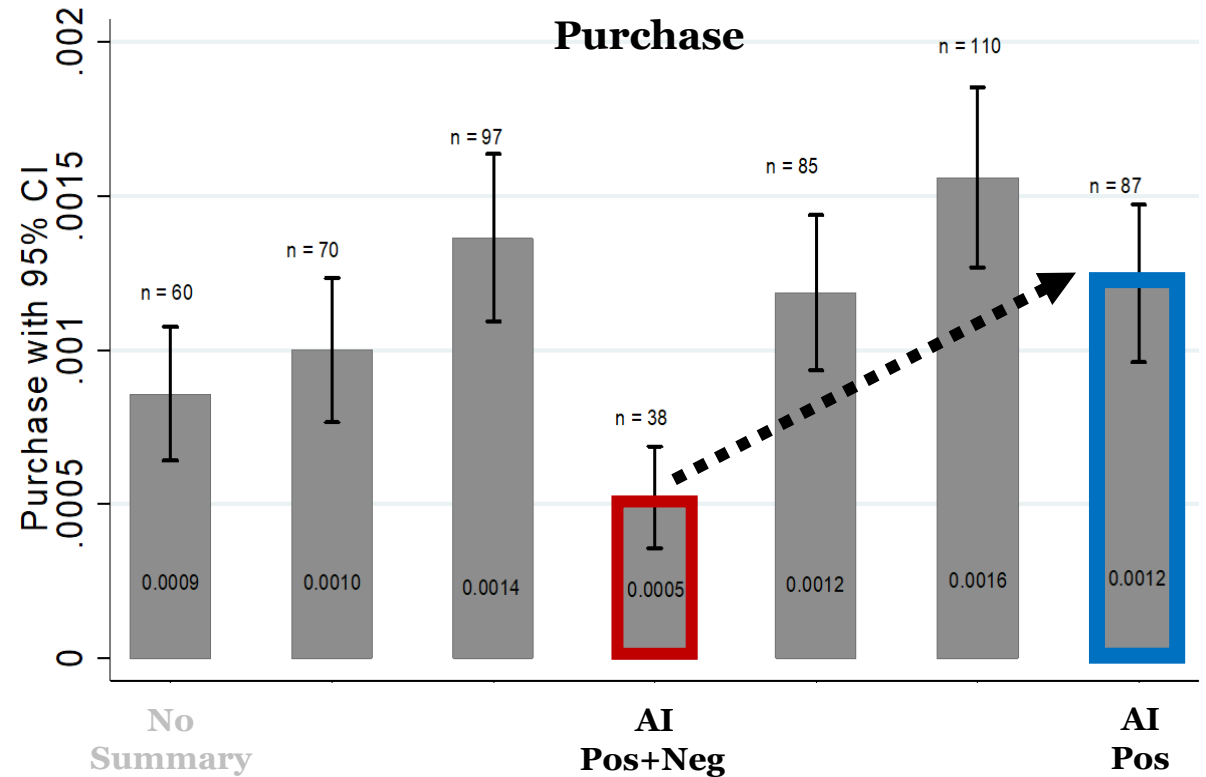
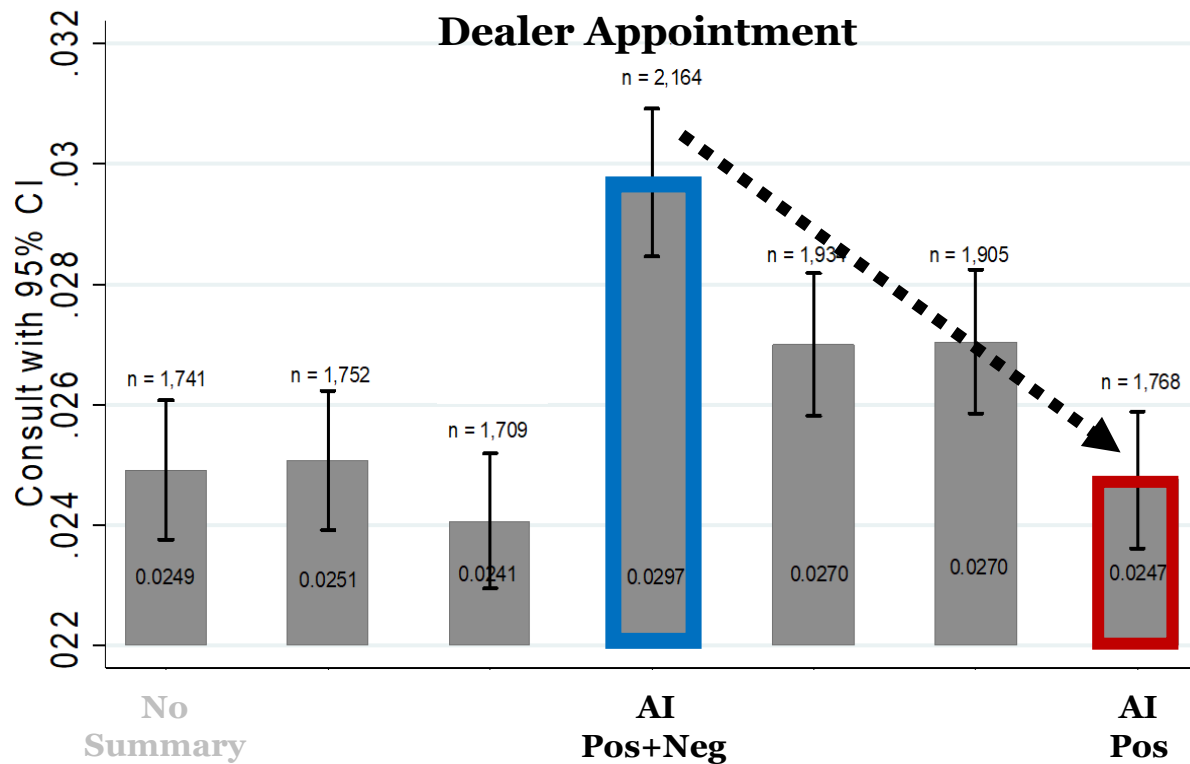
Key Finding (1): AI Disclosure Paradox

AI Disclosure Paradox: Disclosing AI authorship drives engagement in early decision stages (e.g., consideration) but reduces purchase at later stages (e.g., conversion).



Key Finding (2): Interaction Between AI Disclosure and Content Framing

AI disclosure effects differ depending on content framing: When the summary is positive-only, AI disclosure **reduces** early-stage engagement but **boosts** purchase at later stages.



Empirical Analyses: Effects on Consultation and Purchase

Table 1. Estimated Results for the Effectiveness of Review Summary (Baseline: Group 2)

Content Framing	Group	Consideration (<i>Dealer Appointment</i>)	Conversion (<i>Purchase</i>)
<i>Both Positive and Negative</i>	<i>Group 3 (Human-labeled Review Summary)</i>	-0.019 (0.019)	0.085* (0.050)
	<i>Group 4 (AI-labeled Review Summary)</i>	0.089*** (0.018)	-0.204*** (0.060)
<i>Positive-only</i>	<i>Group 5 (Positive-only Review Summary)</i>	0.041** (0.019)	0.040 (0.051)
	<i>Group 6 (Human-labeled & Positive-only Review Summary)</i>	0.031* (0.018)	0.129*** (0.049)
	<i>Group 7 (AI-labeled & Positive-only Review Summary)</i>	-0.007 (0.019)	0.057 (0.051)
<i>Control Variables</i>		YES	YES
<i>Constant</i>		-2.595***	-1.963*
<i>Log-likelihood</i>		-48,155	-48,155
<i>Observations</i>		427,368	427,368

Notes. Bivariate probit with correlated errors; jointly estimated. Standard errors are clustered at the individual level; Significant values are in boldface and * indication.

Why Does the AI Disclosure Paradox Occur?

AI-
Generated

Common Starting Point

Consumers perceive AI as having systematically processed a large volume of consumer reviews. This increases the **perceived credibility** of the entire summary, for both **strengths** and **weaknesses**.



Consideration Dealer Appointment

AI credibility makes the product's **strengths** compelling enough to **consider seriously**, while the credibly reported **weaknesses** motivate consumers to **seek more information** before deciding.



Conversion Purchase

At the point of committing ~\$62,000, **negative evaluations** weighs disproportionately more (**loss aversion**). AI-flagged **weaknesses** are seen as **widespread, systematic issues**, amplifying downside risk and anticipated regret.

Key Insight: The same AI credibility that makes the product **worth exploring** also makes its weaknesses feel **too risky** to accept at the point of purchase.

Supporting Evidence: Moderating Effects by Review Rating and Volume

Higher **review ratings** and higher **review volume intensify** the **AI disclosure paradox**, strengthening both the positive effect on consideration and the negative effect on purchase.

Review Rating

For AI-labeled balanced summaries (G3)

The estimated coefficient of [$G3 \times \ln(\text{ReviewRating})$]:

Consultation
+0.220**

Purchase
-1.269***

Higher ratings create a sharper contrast between the product's strong reputation and AI-flagged weaknesses.

Credibly presented strengths become even more compelling to explore (consideration ↑), while credibly presented weaknesses feel more consequential against an otherwise positive backdrop (purchase ↓).

Review Volume

For AI-labeled balanced summaries (G3)

The estimated coefficient of [$G3 \times \ln(\text{ReviewVolume})$]:

Consultation
+0.023**

Purchase
-0.204***

More reviews reinforce the belief that AI has processed a larger, more comprehensive dataset.

This makes both the strengths and weaknesses in the summary feel more representative and data-supported, strengthening the credibility mechanism in both directions.

Policy Implications for Regulators

Blanket Mandates May Backfire

AI labeling increases product consideration but suppresses purchase.
A one-size-fits-all disclosure requirement may hurt platform economics.

Principle-Based Flexibility

Regulators should consider flexibility in *when* and *how* disclosure is phrased.
Hybrid formats (e.g., “*AI-generated and human editor-curated*”) merit further investigation.

Stage-Dependent Disclosure Design

Strategies effective at the consideration stage may not work at the purchase stage.
Policy design should account for the *consumer’s position* in the *decision funnel*.

*We suggest that well-meaning disclosure mandates can produce **unintended economic consequences** that deserve careful consideration in policy design.*

THANK YOU!

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