Executive Summary

AI improves shopping efficiency but lacks personalization

Method: Qualitative Thematic Analysis
Many respondents appreciate AI's ability to surface relevant products quickly, saving time. However, they note AI often recommends repetitive or previously purchased items, failing to adjust to evolving preferences.

Exposure to AI recommendations increases purchase intent

Method: Independent Samples T-Test
Participants exposed to AI-generated suggestions (Treatment 2) were significantly more likely to report purchase intent ($p = .007$). This validates the influence of AI exposure on shaping consumer behavior.

No significant link between Prime status and AI purchase behavior

Method: Chi-Square Test
Analysis showed no statistically significant relationship between Prime membership and frequency of purchasing AI-recommended products ($p = .417$), suggesting Prime users don't behave differently in this context.

Prime users and AI likers show higher influence probability

Method: Logistic Regression
Respondents who used to be Prime members were 4.6x more likely to be influenced by AI recommendations ($p = .080$), and those who liked AI trended toward significance ($p = .103$), indicating promising directional patterns.

User engagement is shaped by distinct attitudinal segments

Method: Cluster Analysis + PCA
Three groups emerged: Loyal Adoptees, Cautious Explorers, and Skeptical Bystanders. These segments differ in trust, frequency, and openness to AI, reinforcing the need for personalized recommendation strategies.

Low multicollinearity enables clear modeling

Method: Correlation Matrix
Correlation analysis showed no pair of variables exceeded $r = 0.6$, confirming that predictors like trust, helpfulness, and personalization quality measure distinct constructs and are suitable for further regression modeling.

SITUATION OVERVIEW

Unlocking Growth Through Smarter AI Recommendations

Market Context: External Competition

- **Global Leadership:** Amazon generated $638B in revenue (2024), with the U.S. accounting for 60.8%.
- **Competitive Pressure:** In cross-border e-commerce, Amazon leads with 24%, but is closely followed by Temu (21%) and AliExpress (10%).
- **User Base Saturation:** 75% of U.S. customers are Prime members, so growth must now come from deepening engagement, not just acquisition.

Online Retailers from which global shoppers made in their most recent cross-border purchase in 2024

Internal Capability: AI Recommendation System

- **Established Advantage:** Drives 35% of Amazon purchases
- **Recommendation Engine:** Combines collaborative filtering (user-user similarity), content-based filtering (product similarity), and hybrid models
- **Data-Driven Learning:** browsing history, purchases, and user behavior

Problem: Unclear Impact and Competitive Risk

- **Effectiveness Gap:** Impact on purchase frequency, basket size, and satisfaction is not well understood
- **Segment Variability:** Differences in response across customer segments remain unknown

Strategic Opportunity: Deepen Engagement Through Smarter AI

The research project aims to answer: "How do AI-driven recommendations impact purchase behavior and customer retention for Amazon? " We hypothesize that **by enhancing perceived value and convenience, these recommendations increase purchase frequency and transaction value, ultimately driving higher engagement with the platform.** To support this, the study focuses on **THREE strategic areas**:

- **Customer Behavior Insights:** Analyze how AI-driven recommendations influence shopping behavior across different customer segments.
- **Recommendation Effectiveness:** Assess the impact of AI-driven recommendations on decision-making and transaction value.
- **Optimization Strategy:** Identifying key customer expectations and preferences to guide improvements in Amazon's AI-powered recommendation system.

QUALITATIVE DISCOVERY

Uncovering User Mindsets: Qualitative Insights into AI Shopping Behavior

These emerging themes guided our quantitative analysis. We tested whether these perceptions—such as trust, personalization, and usage frequency—predict actual behavior through statistical models.

1

Efficiency ≠ Engagement

Users appreciate the convenience of AI suggestions but often continue manual research for reassurance and control.

2

Repetition Reduces Trust

When recommendations feel repetitive or irrelevant, users disengage, perceiving AI as lazy or sales-driven.

3

AI Drives Discovery, Not Frequency

While users discover new products or brands, AI rarely increases overall shopping frequency or platform loyalty.

4

Conditional Trust in AI

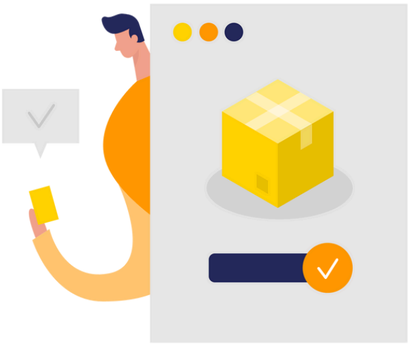
Most users don't mind sharing data, but trust depends on perceived relevance, diversity, and transparency.

User Segmentation Emerged

- Skeptical Researchers: Distrust algorithmic bias, prefer reviews
- Convenience-Driven Shoppers: Want quick, low-effort suggestions
- Tech-Savvy Explorers: Desire innovation and interactivity (e.g., chatbot AI)
- Brand-Loyal Traditionalists: Prefer curated bestsellers, resist novelty

Future Expectations

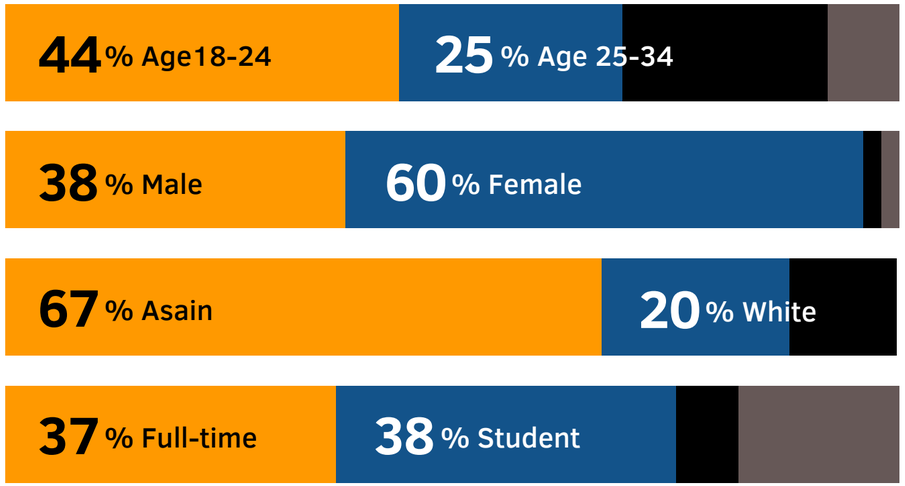
Users envision AI becoming smarter and more assistive, offering personalized filters, better product variety, and even chat-based support.



METHODOLOGY

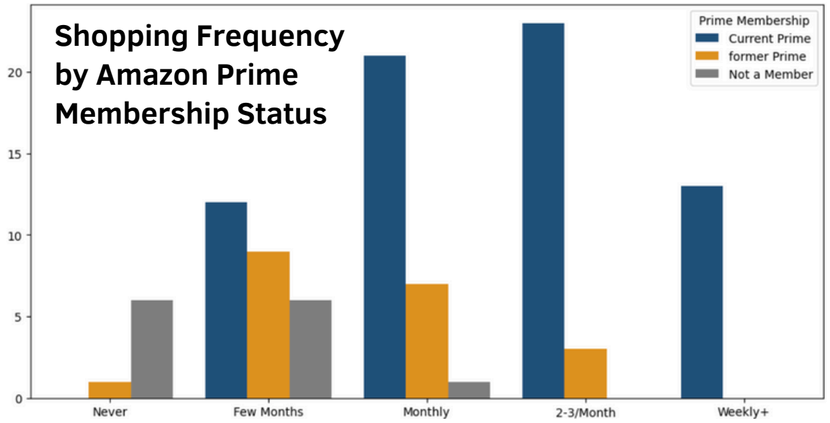
Respondent Profile:

Demographics



Amazon Usage Behavior

68 % current Prime **20** % former Prime



Research Design

1 Survey Design

Closed-ended 5-point Likert questions were used in a between-subjects design. Participants were randomly assigned to control or treatment mockups to compare their effects on key outcomes.

- **Survey Platform:** Qualtrics
- **Survey Duration**: 7 days
- **Data Analysis:** Python, JMP, Excel, Tableau

2 Subject Selection

Screening Criteria: Participants were Amazon users and had made at least one purchase in the past six months.

- **Qualified Responses:** 102
- **Control vs Treatment:** 51% vs 49%

3 Analysis Model

- **Chi-Square Test** – Tested association between Prime status and AI-driven purchase behavior.
- **T-Test** – Compared control vs. treatment group responses to AI recommendations.
- **Logistic Regression** – Predicted AI influence using trust, Prime status, and helpfulness.
- **Correlation Matrix** – Checked for multicollinearity among key variables.
- **Cluster Analysis** – Identified user segments based on AI trust and engagemen

METHODOLOGY

Survey Design

Independent Variables

Amazon Usage

Measures engagement with the platform, including: Shopping frequency, Prime membership status.

Attitude Toward AI

Assesses emotional/cognitive trust in Amazon's AI, including perceived transparency, reliability.

Perception of Recommendations

Evaluates the relevance, diversity, and personalization quality of AI-generated suggestions

Engagement Behavior

Captures user interaction style and perceived usefulness for discovery and decision-making

Overall Satisfaction

Reflects users' overall satisfaction with the shopping experience, including ease and perceived value

Randomized Treatments

Mockups were used to highlight the difference between **standard and AI-personalized recommendations** to test perceived relevance, exploration behavior, and purchase intent.

Control

Standard Recommendation Module

"Customers Who Bought This Also Bought"

Treatment Group

AI-Personalized Recommendation Module

"AI-Personalized Picks for You"

Dependent Variables

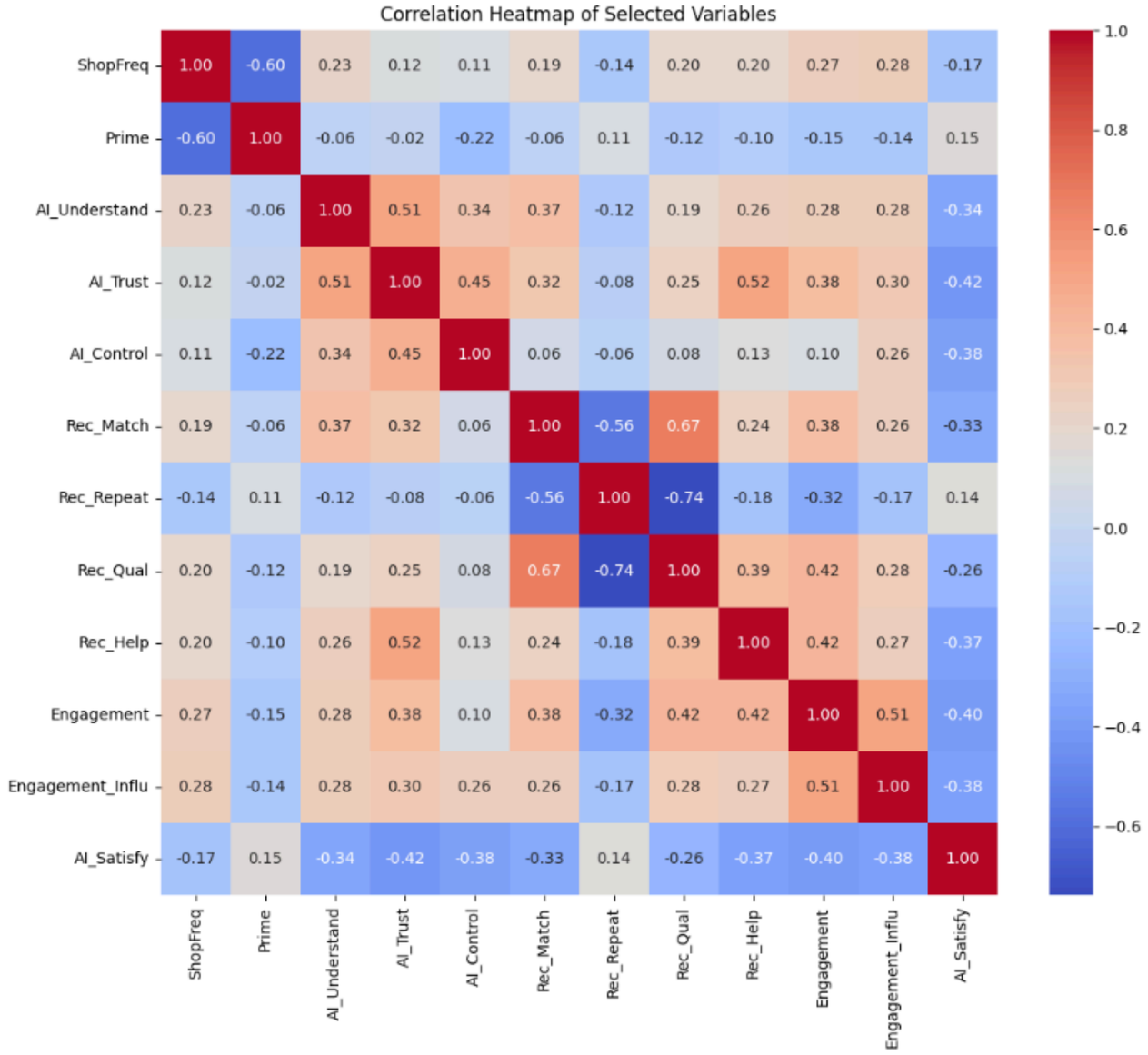
Purchase Behavior

Measures the frequency or likelihood of purchasing items based on AI-generated suggestions.

Mockup Example

ANALYTICAL INSIGHTS

Correlation Analysis: AI Perceptions, Behavior, and Demographics



Result Interpretation

- The heatmap visualizes Spearman correlations among variables related to AI perception, behavioral intent, and demographics.
- No variable pair exceeds r = 0.6, meaning there is no strong multicollinearity in the dataset.
- All variables appear to be measuring distinct, non-overlapping constructs.

Insights

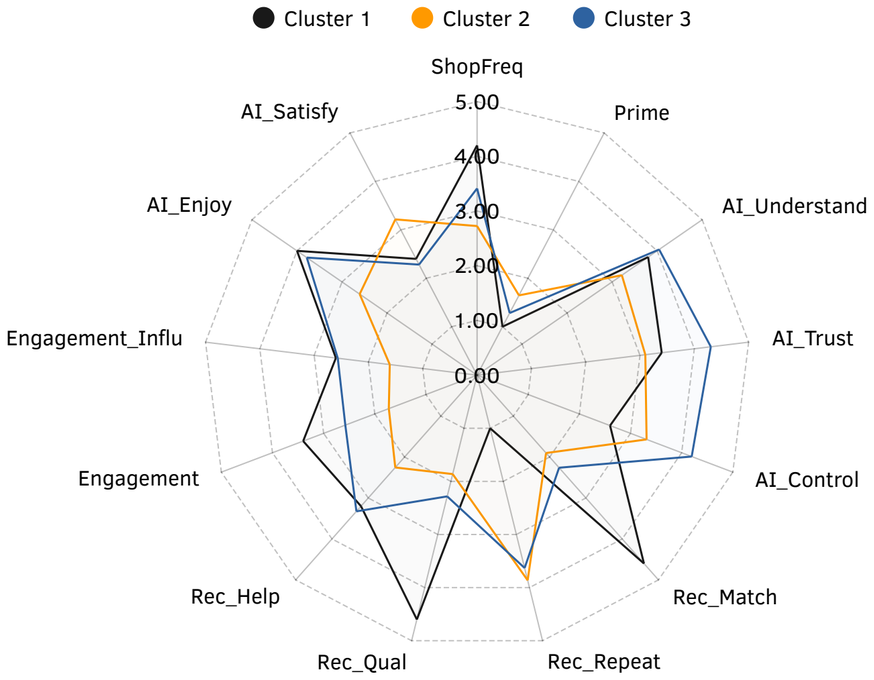
- Since variables are not highly correlated, they can be confidently included in regression or clustering models without concern for redundancy.
- Behavioral variables (e.g., trust, personalization quality, helpfulness) show moderate positive relationships with each other and with satisfaction and purchase behavior.
- Demographics such as age, gender, and race have weak or no correlation with AI-related responses, suggesting behavioral differences are not primarily driven by demographics.
- This supports the continued use of these variables as independent predictors in future analyses such as logistic regression, segmentation, or causal modeling.

ANALYTICAL INSIGHTS

Cluster Analysis: Segmenting Consumers by AI Recommendation Response

Cluster	AI Recommendation Attitude	Engagement Level
The AI-Engaged Navigators (Cluster 1)	Trust AI, value variety + relevance	High usage, high enjoyment
Skeptical Validators (Cluster 2)	Distrust AI, prefers manual search	Low engagement, sees repetition
Informed Optimists (Cluster 3)	Understand AI, appreciate control	Moderate use, high trust

Interviewee Profiles and Behavioral Patterns



Cluster Interpretation & Behavioral Insights

From the dataset, users can be segmented into three distinct groups, with attitudes toward AI roughly split between positive and skeptical:

- **Cluster 1 (50%): The AI-Engaged Navigators** - Active, exploratory users who rely on and trust AI to enhance shopping decisions. Best audience for new feature rollouts and early personalization adoption.
- **Cluster 2 (45%): The Skeptical Validators** - Low-engagement segment that's wary of AI, likely to ignore or dismiss recommendations. Need transparency, explainability, and value proof.
- **Cluster 3 (5%): The Informed Optimists -** Tech-savvy, trusting users who are comfortable with AI and value its utility. A good target for advanced filters, explanatory cues, and beta testing AI features.

Comparison with Qualitative Segmentation

There's strong alignment between quantitative and qualitative methods for core segments like **skeptics and innovators**. However, **Brand-Loyal Traditionalists** are less visible in quantitative clustering, suggesting their behaviors may be less attitudinal and more context-specific.

ANALYTICAL INSIGHTS

Chi-Square Test

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
Q2 * Q6	102	100.0%	0	0.0%	102	100.0%

Q2 * Q6 Crosstabulation

			Q6				
			1	2	3	4	Total
Q2	1	Count	6	26	27	10	69
		Expected Count	6.8	28.4	25.7	8.1	69.0
		% within Q2	8.7%	37.7%	39.1%	14.5%	100.0%
	2	Count	2	12	6	0	20
		Expected Count	2.0	8.2	7.5	2.4	20.0
		% within Q2	10.0%	60.0%	30.0%	0.0%	100.0%
	3	Count	2	4	5	2	13
		Expected Count	1.3	5.4	4.8	1.5	13.0
		% within Q2	15.4%	30.8%	38.5%	15.4%	100.0%
Total		Count	10	42	38	12	102
		Expected Count	10.0	42.0	38.0	12.0	102.0
		% within Q2	9.8%	41.2%	37.3%	11.8%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	6.055[a]	6	.417
Likelihood Ratio	8.150	6	.227
Linear-by-Linear Association	.843	1	.359
N of Valid Cases	102		

a. 5 cells (41.7%) have expected count less than 5. The minimum expected count is 1.27.

Objective

To check if there is a relationship between Prime membership (Q2) and influence by recommendations (Q6)?

- Q2 - Are you an Amazon Prime member?
- Q6 - How often do you buy products recommended by AI?

Result Interpretation

- The Chi-square test showed no statistically significant relationship between Amazon Prime membership status (Q2) and frequency of purchasing AI-recommended products (Q6).
- Pearson Chi-Square: $\chi^2(6) = 6.055$, $p = .417$
- With $p > .05$, we fail to reject the null hypothesis.
- This suggests that Prime members are not significantly more likely than non-members to purchase AI-recommended products.

Insights

- **Prime status alone is not a reliable predictor** of engagement with AI recommendations.
- This implies that **other factors—such as trust in AI, personalization quality, or shopping behavior**—may be more influential drivers of AI-based purchase behavior.
- Consider **targeting specific engagement mindsets (e.g., Loyal Adoptees or Cautious Explorers)** rather than relying solely on membership tier.

ANALYTICAL INSIGHTS

T-Test: Behavioral Response to AI vs. Non-AI Product Suggestions

Objective

To test if there's a statistically significant difference in responses to Q14 between those exposed to AI-generated recommendations (Treatment 2 -Test Group) and non-AI (Treatment 1 - Control Group).

We wanted to compare the average responses (mean) of the control and test groups to Q14. This t test measures "Is there a statistically significant difference in purchase behavior between those exposed to AI recommendations and those not?"

Result Interpretation

- The t-test comparing Q14 responses between the control (non-AI) and treatment (AI) groups revealed a statistically significant difference.
- t(100) = 2.739, p = .007 (equal variances assumed)
- Participants exposed to AI-generated recommendations (Treatment 2) reported higher likelihood of acting on suggestions than those in the control group.
- This supports the hypothesis that AI can positively influence consumer purchase decisions.

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
Q14_1	Equal variances assumed	28.561	<.001	2.739	100	.004	.007	.243	.089	.067	.419
	Equal variances not assumed			2.753	95.872	.004	.007	.243	.088	.068	.418

Insights

- **AI exposure drives behavioral change**: Those who saw AI-powered suggestions were more responsive than those who didn't.
- Cohen's d = 0.448, indicating **a small to medium effect size**—while not drastic, the difference is meaningful and consistent with real-world marketing impact.
- This reinforces **the strategic value of AI personalization** in enhancing recommendation effectiveness.
- **Future applications**: Targeting skeptical or passive segments (e.g., "Cautious Explorers") with AI-powered visuals could encourage higher purchase engagement.

Group Statistics

	Treatment	N	Mean	Std. Deviation	Std. Error Mean
Q14_1	1	52	1.42	.499	.069
	2	50	1.18	.388	.055

Independent Samples Effect Sizes

		Standardizer[a]	Point Estimate	95% Confidence Interval Lower	95% Confidence Interval Upper
Q14_1	Cohen's d	.448	.543	.146	.937
	Hedges' correction	.451	.538	.145	.930
	Glass's delta	.388	.626	.216	1.031

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control (i.e., the ...

ANALYTICAL INSIGHTS

Logistic Regression: Predicting AI Impact on Consumer Exploration

Objective

- Predict whether someone was influenced by AI recommendations (Yes/No) based on factors like:
  - Prime membership (Q2)
  - Shopping frequency (Q1)
  - Trust in AI recommendations (Q3)
  - Perceived helpfulness (Q5)
  - Purchase frequency based on AI (Q6)
- Dependent variable - Q11: “Did the recommendations influence you to explore products you wouldn’t have otherwise considered?”
  - 1.Yes = 1
  - 2.No = 0

Result Interpretation

- The logistic regression model predicts whether users were influenced by AI recommendations to consider new products.
- Overall model significance: p = .062 → just above the standard threshold (p < .05), so not statistically significant but very close.
- Model fit: Nagelkerke R^2 = 0.181 → The model explains 18.1% of the variance in influence behavior.
- Classification accuracy: 61.8% overall, better at predicting “No” (67.9%) than “Yes” (54.3%).

Insights

- **Former Prime Members (Q2(2)) are 4.6x more likely to be influenced by AI recommendations**, with marginal significance (p = .080).
- **Liking or enjoying AI suggestions (Q3_3)** also trends toward significance (p = .103), indicating that positive emotional response may drive influence.
- The model almost reaches statistical significance (p = .062), suggesting that with a larger sample size or refined predictors, results could become conclusive.
- Although not definitive, the model provides directional insights: **Prior Prime membership and positive perception of AI** may be key factors in nudging behavior.
- Future testing with increased power is encouraged to validate these early patterns.

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	14.842	8	.062
	Block	14.842	8	.062
	Model	14.842	8	.062

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	125.578[a]	.135	.181

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Classification Table[a]

			Predicted		
			Q11		
	Observed		1	2	Percentage Correct
Step 1	Q11	1	25	21	54.3
		2	18	38	67.9
	Overall Percentage				61.8

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Q1	.293	.253	1.342	1	.247	1.340
	Q2			4.680	2	.096	
	Q2(1)	-.424	.626	.460	1	.498	.654
	Q2(2)	1.536	.877	3.065	1	.080	4.646
	Q3_1	.204	.250	.666	1	.414	1.226
	Q3_2	.084	.334	.063	1	.802	1.087
	Q3_3	.429	.263	2.666	1	.103	1.536
	Q5	-.089	.284	.098	1	.754	.915
	Q6	-.390	.310	1.587	1	.208	.677
	Constant	-1.229	1.595	.594	1	.441	.292

Recommendation

Strategic Recommendations: Improving AI Recommendation Effectiveness

Short-Term Implementation (0–6 months)

These focus on quick wins using existing infrastructure and insights.

1. **Diversify AI Recommendations**
   - Reduce repetition and over-targeting by rotating categories, brands, and formats.
   - Use lightweight models to flag and rotate out duplicate suggestions across sessions.
2. **Add Explainer Labels ("Why this product?")**
   - Show micro-copy like “Because you bought…” or “Trending in your location.”
   - Builds trust and perceived transparency—especially for “Skeptical Researchers.”
3. **Introduce Filter Options**
   - Add optional filters like price range, category, or brand to the recommendation panel.
   - Empowers “Tech-Savvy Explorers” and increases engagement by giving control.

Long-Term Implementation (6–18 months)

These require deeper product or algorithm enhancements and system-level changes.

1. **Segment-Based Personalization Strategy**
   - Cluster users into personas like “Loyal Adoptees” vs. “Cautious Explorers” and serve tailored AI strategies (e.g., curated vs. exploratory recs).
   - Apply behavioral scoring models that adapt based on interaction over time.
2. **Contextual Personalization**
   - Move beyond static browsing data—incorporate context signals like time of day, session length, or seasonal trends for relevance.
   - Improves perceived novelty and mitigates “repetition fatigue.”
3. **Feedback Loop Integration**
   - Allow users to thumbs up/down, hide, or save recommendations to train the model passively.
   - Supports dynamic learning and promotes perceived user control.

LIMITATION

Limitations to Consider

1. Sample Size (N = 102)

- **Limitation**: The sample size is relatively small, especially for subgroup or treatment-effect analysis (e.g., regression, Chi-square).
- **Influence**: Some statistical tests (e.g., logistic regression, p = .062) approached significance but didn't meet the threshold, possibly due to limited power. A larger sample might reveal clearer, more generalizable effects.

2. Self-Reported Measures

- **Limitation**: All data comes from self-reported surveys, which may suffer from social desirability bias or inaccurate recall.
- **Influence**: Users might overstate how much they engage with or trust AI, affecting the validity of behavioral insights (e.g., purchase intent, engagement frequency).

3. Limited Behavioral Tracking

- **Limitation**: The study lacks actual behavioral data (e.g., clickstream or purchase logs from Amazon).
- **Influence**: Limits the ability to connect stated preferences to real-world actions. Some attitudes (like liking AI) may not convert to action (like actual purchases).

4. Controlled Mockups vs. Real Context

- **Limitation**: Treatments were based on static mockups rather than interactive AI experiences.
- **Influence**: May not fully reflect how users behave in a live shopping environment, especially regarding real-time feedback loops or AI adaptivity.

5. Limited Demographic Diversity

- **Limitation**: While demographics were collected, the analysis didn’t deeply explore their influence (e.g., age × AI trust).
- **Influence**: Missed opportunity to identify nuanced insights across diverse shopper profiles (e.g., Gen Z vs. Boomers or students vs. working professionals).

6. Measurement Design Constraints

- **Limitation**: Certain constructs (like satisfaction or trust) were measured using only 1–2 items.
- **Influence**: Reduces reliability and makes it harder to perform factor analysis or scale validation, potentially weakening correlation or regression findings.

Appendix

Survey

How often do you shop on Amazon?

- ◯ Never
- ◯ Once every few months
- ◯ Once a month
- ◯ 2-3 times a month
- ◯ Weekly or more

What is your current Amazon Prime membership status?

- ◯ I am a current Prime Member
- ◯ I used to be a Prime Member
- ◯ I have never been a Prime Member

How do you typically engage with Amazon's AI-generated recommendations? (Select all that apply)

- ☐ I ignore them
- ☐ I occasionally browse them but rarely click
- ☐ I click on recommendations to learn more about the product
- ☐ I add recommended items to my cart but don't always purchase
- ☐ I frequently purchase recommended products

To what extent do you agree with the following statement: "Amazon's AI recommendations make my shopping experience easier and more enjoyable."

- ◯ Strongly disagree
- ◯ Somewhat disagree
- ◯ Neither agree nor disagree
- ◯ Somewhat agree
- ◯ Strongly agree

Which of the following best describes your overall satisfaction with Amazon's AI-generated product recommendations?

- ◯ I find them very helpful and frequently rely on them
- ◯ They are somewhat useful, but I still prefer browsing manually
- ◯ I use them occasionally, but they don't impact my decisions much
- ◯ They rarely provide value, and I mostly ignore them
- ◯ They are completely irrelevant to my shopping needs

When browsing Amazon, how helpful do you find the product recommendations in discovering something new or useful?

- ◯ Not at all helpful
- ◯ Slightly helpful
- ◯ Moderately helpful
- ◯ Very helpful
- ◯ Extremely helpful

To what extent do you agree or disagree with the following statements about Amazon's product recommendations?

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
I understand how Amazon's AI selects recommendations for me.	◯	◯	◯	◯	◯
I feel confident that Amazon's recommendations are reliable and helpful.	◯	◯	◯	◯	◯
I feel I can influence or personalize the recommendations I receive.	◯	◯	◯	◯	◯

How well do the following statements describe your experience with Amazon's recommendations?

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
The product suggestions match what I actually need.	◯	◯	◯	◯	◯
I often see the same items being recommended over and over.	◯	◯	◯	◯	◯
The recommendations feel tailored to my preferences.	◯	◯	◯	◯	◯

How often do you purchase products directly based on Amazon's recommendations (e.g., "Recommended for you", "Customers also bought")?

- ◯ Never
- ◯ Rarely
- ◯ Occassionally
- ◯ Frequently
- ◯ Almost every time I shop

How much do AI-generated recommendations influence your final purchase decisions on Amazon?

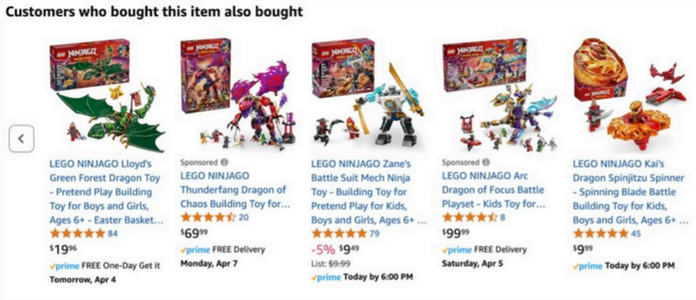
- ◯ None at all
- ◯ A little
- ◯ A moderate amount
- ◯ A lot
- ◯ A great deal

Appendix

Survey

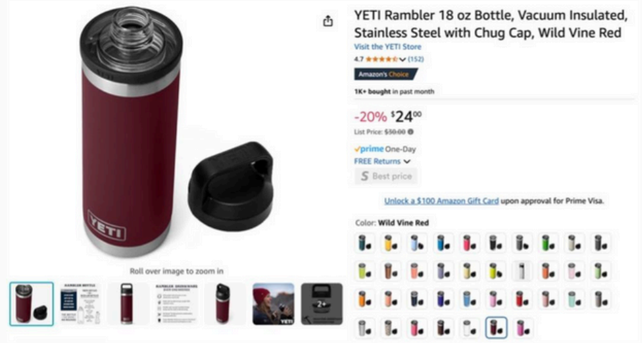
Did the recommendations in the image influence you to consider products you wouldn't have otherwise considered?

- ◯ Yes
- ◯ No



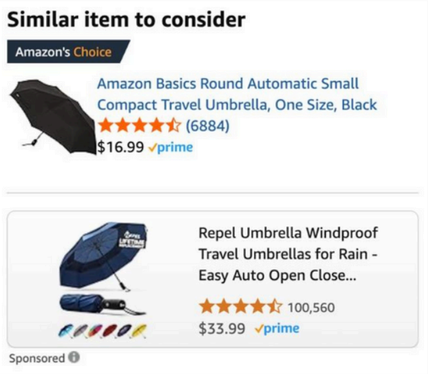
To what extent do you believe this AI recommendation was personalized?

- ◯ Not at all personalized
- ◯ Slightly personalized
- ◯ Moderately personalized
- ◯ Very personalized
- ◯ Extremely personalized



When considering the product 'Yeti Insulated Water Bottle', which would you prefer?

- ◯ Buy it individually now
- ◯ Buy it as part of a bundle with a complementary product for a discount
- ◯ Wait for a sale on the individual product



How likely are you to be influenced by the above for your purchase?

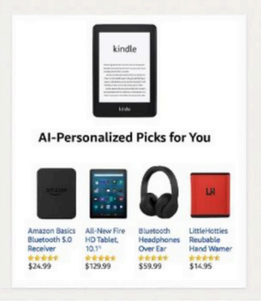
- ◯ Extremely unlikely
- ◯ Somewhat unlikely
- ◯ Neither likely nor unlikely
- ◯ Somewhat likely
- ◯ Extremely likely

How important are other customers' opinions when you make purchase decisions online?

- ◯ Not at all important
- ◯ Slightly important
- ◯ Moderately important
- ◯ Very important
- ◯ Extremely important

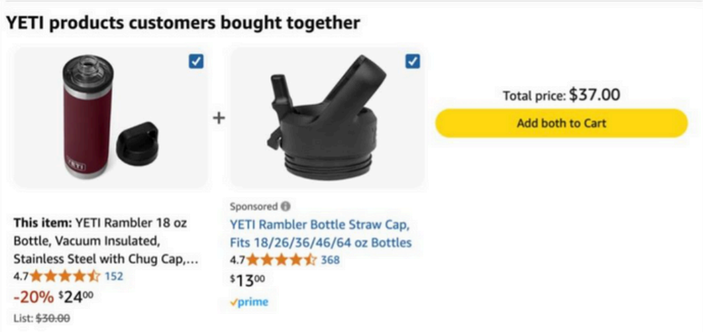
Appendix

Survey



Did the recommendations in the image influence you to consider products you wouldn't have otherwise explored?

- ◯ Yes
- ◯ No



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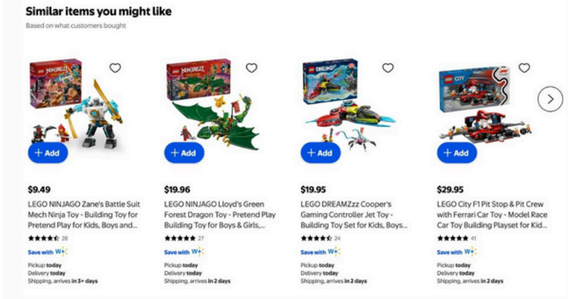
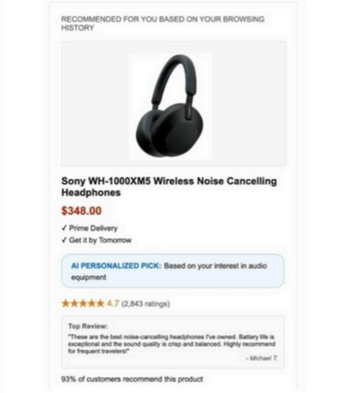
- ◯ Wait for a sale on the individual product



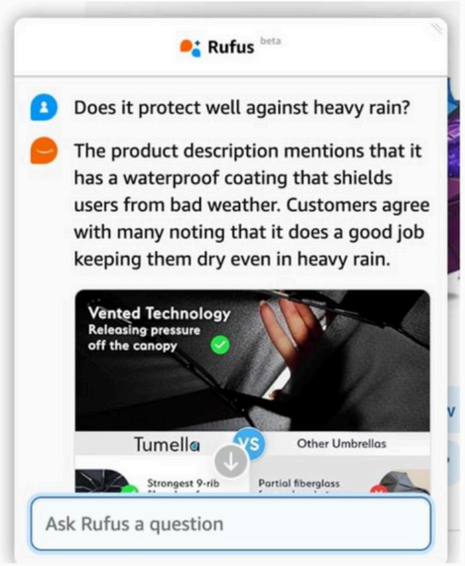
To what extent do you believe this AI recommendation was personalized?

- ◯ Not at all personalized
- ◯ Slightly personalized
- ◯ Moderately personalized
- ◯ Very personalized
- ◯ Extremely personalized



How important are other customers' opinions when you make purchase decisions online?

- ◯ Not at all important
- ◯ Slightly important
- ◯ Moderately important
- ◯ Very important
- ◯ Extremely important



How likely are you to be influenced by the above for your purchase?

- ◯ Extremely unlikely
- ◯ Somewhat unlikely
- ◯ Neither likely nor unlikely
- ◯ Somewhat likely
- ◯ Extremely likely

Appendix

Survey

Your Name:

Age:

- Under 18
- 18 - 24
- 25 - 34
- 35 - 44
- 45 - 54
- 55 - 64
- 65 or older

Current Employment Status

- Employed full-time
- Employed part-time
- Student
- Self-employed
- Unemployed
- Retired
- Prefer not to say

Gender:

- Male
- Female
- Non-binary / third gender
- Prefer not to say

Race/Ethnicity:

- White
- Black or African American
- American Indian or Alaska Native
- Asian
- Native Hawaiian or Pacific Islander
- Other: (please specify)
- Prefer not to say