Online Appendix

Generative AI and Sales Productivity: Field Experiments in Online Retail

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A Illustrative User Interfaces and Examples of Each Experiment

Pre-sale Service Chatbot In Figure A1, Panel (a) depicts the control condition, where a pre-programmed auto response indicates that no service is available, while Panel (b) presents the treatment condition, featuring support from a GenAI-driven chatbot. The chatbot acts as a virtual sales assistant, available 24/7 to provide instant responses to pre-sale inquiries, covering product features, pricing, availability, and delivery options across multiple languages.

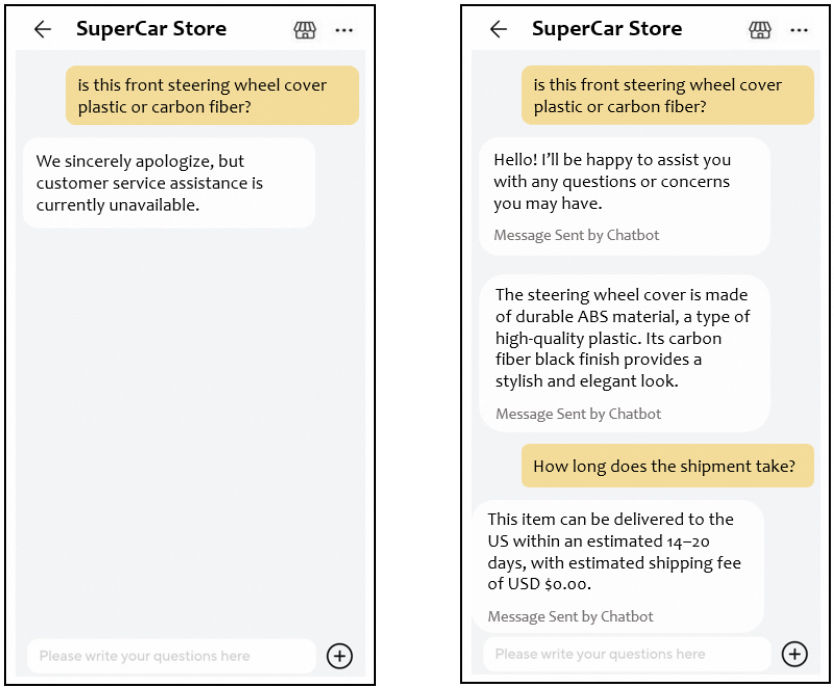
Search Query Refinement In Figure A2, Panel (a) displays the consumer's original search query in Spanish, along with the corresponding results, while Panel (b) presents the structured English query translated and refined by GenAI, as well as the corresponding search results retrieved. The GenAI-powered query refinement can improve the expression of consumer demand and facilitate the matching efficiency of search engines.

Product Description In Figure A3, Panel (a) illustrates the control condition with human-generated descriptions, while Panel (b) shows the treatment condition, where GenAI-created descriptions are layered on top of those written by humans. The AI-generated content provides more comprehensive and structured bullet-point-style descriptions that highlight product features, benefits, and typical use cases.

Marketing Push Message In Figure A4, Panel (a) illustrates a human-generated marketing push message, whereas Panel (b) displays multiple messages produced by GenAI for the same product. Generative AI enables large-scale creation of diverse marketing content, increasing the

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Figure A1: Illustration of Pre-sale Service Chatbot



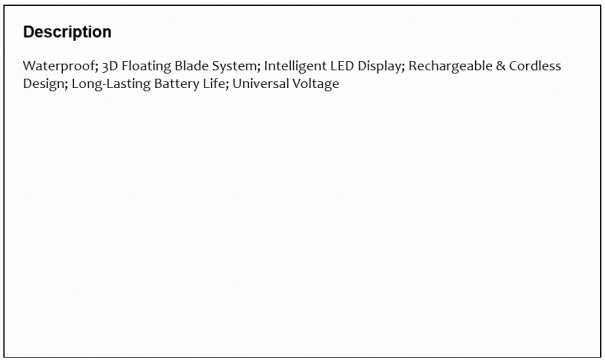
(a) Auto-Response (No Service) (b) GenAI-Driven Chatbot

Figure A2: Illustration of Search Query Refinement

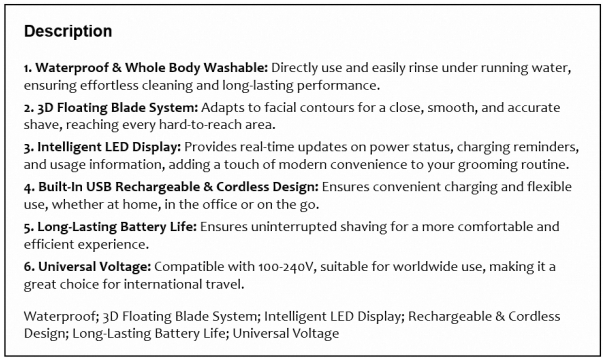


(a) Search Results of Consumer Query (b) Search Results of GenAI-Refined Query

Figure A3: Illustration of Product Description

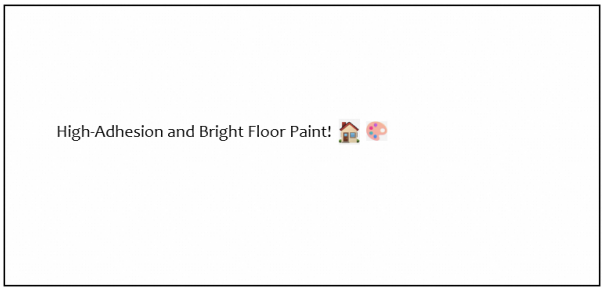


(a) Human-Created Description



(b) GenAI-Created Description Above Original Human Input

Figure A4: Illustration of Marketing Push Message



(a) Human-Created Push Message



(b) GenAI-Created Push Messages

likelihood that consumers encounter differentiated messages and thereby allowing platforms to leverage the benefits of personalized marketing.

Google Advertising Title In this case, GenAI is applied to optimize human-generated product titles for Google advertising. Since the model was not fine-tuned with e-commerce domain knowledge, the performance of GenAI-optimized titles is lower than that of human-generated titles. For example, the original human-generated title for a pair of sunglasses is: "2024 New Arrival Polarized Pitboss 2 Sunglasses Men Cycling Eyewear Goggles Bicycle Glasses". The GenAI-optimized version is: "Men's Polarized Pitboss 2 Sunglasses - Polycarbonate Frame for Cycling, Sports, Bike Goggles Bicycle". On Google Shopping, the first few words of a product title are the most prominent, as shown in Figure A5. Thus, by removing popular keywords such as "New Arrival," GenAI may reduce consumer attention.

Chargeback Defense Figure A6 illustrates the process by which the chargeback defense agent interprets and analyzes consumer claims, gathers relevant evidence—including transaction records,

Figure A5: Illustration of Google Shopping Interface

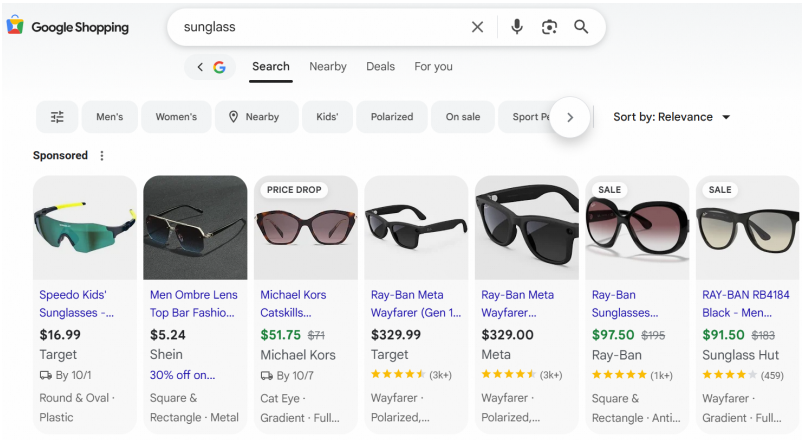
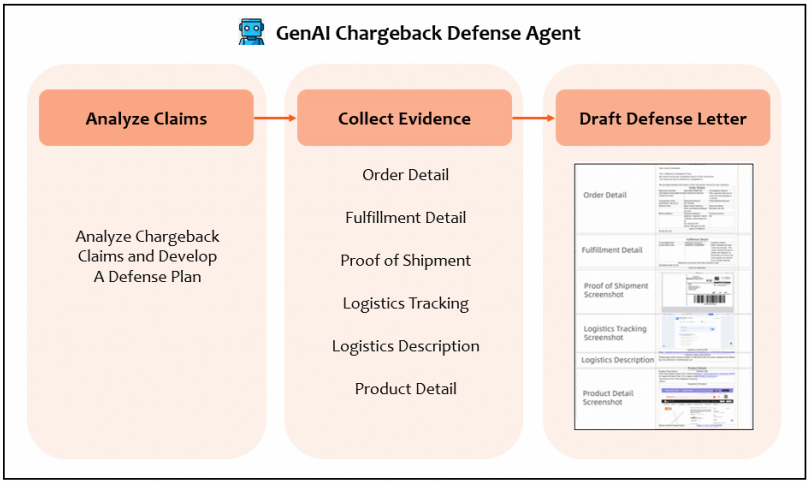


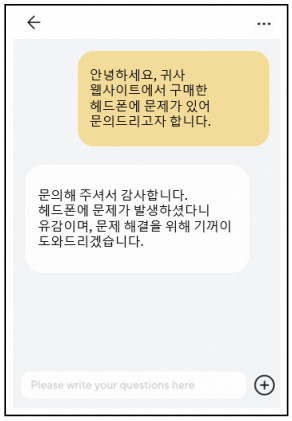
Figure A6: Illustration of Chargeback Defense



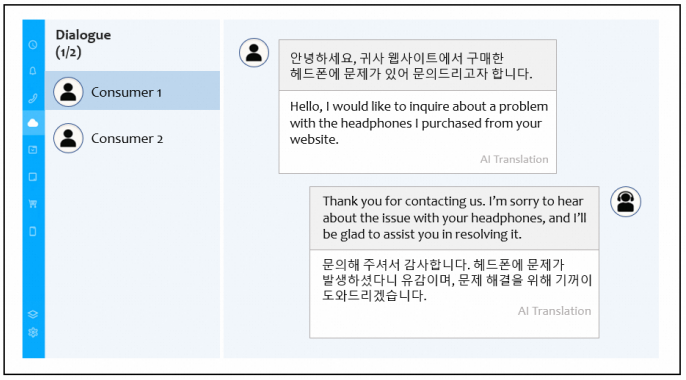
product details, and shipping information—and drafts persuasive defense letters. By automating this complex workflow, GenAI enables sellers to respond to chargeback claims more quickly and consistently, thereby improving win rates while reducing compliance burdens and financial losses.

Live Chat Translation Figure A7 depicts the live chat translation system. Panel (a) shows the consumer interface, where a Korean consumer submits a query. Panel (b) presents the service agent interface, where a Filipino agent receives the query translated in real time from Korean to English by GenAI. The system supports bidirectional translation: the agent's English response is simultaneously translated into Korean, allowing the consumer to receive the reply in their native language. This functionality enables English-speaking Filipino agents to communicate seamlessly with consumers across multiple languages on the platform.

Figure A7: Illustration of Live Chat Translation



(a) Consumer Interface



(b) Customer Service Agent Interface

B Covariate Balance Checks for the Field Experiments

In this section, we present detailed covariate balance checks for each of the five experiments for which granular data are available.

Table B1: Covariate Balance and Randomization Checks

	Control	Treatment	*p-value* (C=T)
Pre-sale Service Chatbot			
Gender	1.000 (0.600)	1.004 (0.598)	0.503
Age Tier	1.000 (0.280)	1.001 (0.277)	0.816
Registered Years	1.000 (0.988)	0.997 (0.957)	0.779
Past Login Days	1.000 (1.071)	1.014 (1.131)	0.220
Past Orders	1.000 (3.108)	0.981 (2.863)	0.528
Past Sales	1.000 (6.441)	1.017 (9.097)	0.833
N. of Consumers	15,457	29,157	
Search Query Refinement			
Gender	1.000 (0.799)	1.001 (0.799)	0.204
Age Tier	1.000 (0.289)	1.000 (0.289)	0.466
Registered Years	1.000 (0.860)	1.001 (0.861)	0.333
Past Login Days	1.000 (1.051)	1.002 (1.054)	0.207
Past Orders	1.000 (3.214)	1.007 (3.468)	0.140
Past Sales	1.000 (6.850)	1.014 (8.206)	0.217
N. of Consumers	929,188	920,194	
Product Description			
Gender	1.000 (0.912)	1.000 (0.912)	0.778
Age Tier	1.000 (0.283)	1.000 (0.283)	0.127
Registered Years	1.000 (0.942)	1.001 (0.942)	0.192
Past Login Days	1.000 (0.942)	0.999 (0.944)	0.490
Past Orders	1.000 (2.437)	1.001 (2.516)	0.627
Past Sales	1.000 (3.613)	0.998 (3.613)	0.515
N. of Consumers	2,392,803	2,380,134	
Marketing Push Message			
Gender	1.000 (0.894)	1.000 (0.894)	0.599
Age Tier	1.000 (0.275)	1.000 (0.277)	0.538
Registered Years	1.000 (1.009)	1.000 (1.008)	0.714
Past Login Days	1.000 (2.386)	0.999 (2.371)	0.501
Past Orders	1.000 (3.304)	1.003 (3.062)	0.157
Past Sales	1.000 (6.115)	1.004 (5.278)	0.157
N. of Consumers	6,869,558	6,845,970	
Google Advertising Title			
Past Sales	1.000 (2.261)	0.993 (2.238)	0.084
Industry ID	1.000 (0.414)	1.000 (0.416)	0.712
N. of Products	621,133	622,883	

[1] Mean (Std. Dev.) are shown with all values normalized by the corresponding variable's control group mean. For the definitions of each variable, refer to the notes in Figure 1 of the main paper.

[2] The first four experiments are conducted at the consumer level and thus the unit of observation is the consumer. The Google Advertising Title experiment is conducted at the product level and thus the unit of observation is the product.

C Main Results: Model, Estimation, and Additional Outcomes

Pre-sale Service Chatbot Pre-sale inquiries regarding product and seller information (e.g., product attributes, promotions, and logistics) play a critical role in shaping consumer purchase decisions. To reduce search costs, support decision-making, improve customer service, and enhance the overall consumer experience, the platform introduced a GenAI-powered chatbot capable of delivering accurate, content-rich responses tailored to a diverse consumer base and available around the clock.

We conduct our analysis using the following regression model:

$$y_i = \beta \times Treat_i + \alpha_{c(i)} + \epsilon_i, \tag{1}$$

where i indicates the consumer, y_i stands for a consumer's outcome (e.g., conversion rate or sales), $Treat_i$ is an indicator for whether the consumer is assigned to the treatment group. Since consumers entered the experiments on different days, we control for their entry-day cohort fixed effects using $\alpha_{c(i)}$.

In addition to the main experiment comparing an auto-response indicating service unavailability ("No Service") with a GenAI chatbot service ("GenAI Reply"), we also studied three supplementary experiments: (1) "No Service" versus "GenAI+Human Reply", where consumers initially interacted with a GenAI chatbot and unresolved issues were escalated to human agents; (2) "Human Reply", where consumers were exclusively served by human agents, versus "GenAI Reply"; (3) "Human Reply" versus "GenAI+Human Reply".

Table C1 presents the impact of the GenAI chatbot on sales, while Table C2 reports its effects on conversion rates and cart value. In both tables, Columns (1)–(2) report effects when the treatment is GenAI Reply, and Columns (3)–(4) report effects for GenAI+Human Reply. Within each set, Columns (1) and (3) use No Service as the control, while Columns (2) and (4) use Human Reply as the control.

Focusing on the comparison between the No Service control and the GenAI Reply treatment (Column 1), we continue to find sizable sales productivity improvements: sales increase by 16.3% and conversion rate rises by 21.7% (both significant at the 1% level). Using Human Reply as the control (Column 2), the GenAI Reply treatment shows no statistically significant differences in either sales or conversion, suggesting that the GenAI chatbot matches the quality of human service but does not outperform it. When the No Service control is compared with the GenAI+Human Reply treatment (Column 3), the gains are even larger—sales improve by 25.0% and conversion by 29.0%—indicating complementarities between GenAI and human agents. By contrast, relative to the Human Reply control (Column 4), the GenAI+Human Reply treatment yields a marginally

significant 11.5% increase in sales, with no statistically significant change in conversion (4.8%), implying that the hybrid approach can enhance revenue even when benchmarked against human agents. Finally, Table C2 shows that all estimated effects on cart value are statistically insignificant.

Table C1: Effects of Pre-sale Service Chatbot on Sales Across Experiments

Treatment:	GenAI Reply	GenAI Reply	GenAI+Human Reply	GenAI+Human Reply
Control:	No Service	Human Reply	No Service	Human Reply
	(1)	(2)	(3)	(4)
Treat	0.274***	0.0701	0.422***	0.218*
	(0.0970)	(0.0967)	(0.115)	(0.114)
%Change	16.25%	3.71%	25.03%	11.53%
Observations	44,614	44,736	30,345	30,467
R-squared	0.000	0.000	0.000	0.000

[1] "Sales" represents the total expenditure on product orders.
[2] Standard errors are in parentheses. % Change is calculated by dividing the treatment effect by the control group mean. *** p<0.01, ** p<0.05, * p<0.1.

Table C2: Conversion Rate and Cart Value in Pre-sale Service Chatbot Experiments

Treatment:	GenAI Reply	GenAI Reply	GenAI+Human Reply	GenAI+Human Reply
Control:	No Service	Human Reply	No Service	Human Reply
	(1)	(2)	(3)	(4)
Extensive margin: Conversion Rate				
Treat	0.0131***	-0.000768	0.0175***	0.00358
	(0.00252)	(0.00259)	(0.00291)	(0.00304)
%Change	21.70%	-1.03%	28.99%	4.82%
Observations	44,614	44,736	30,345	30,467
R-squared	0.001	0.000	0.001	0.000
Intensive margin: Cart Value (conditional on purchase)				
Treat	-1.264	1.220	-0.859	1.624
	(1.036)	(0.929)	(1.203)	(1.078)
%Change	-4.52%	4.79%	-3.08%	6.38%
Observations	3,076	3,300	2,092	2,316
R-squared	0.000	0.001	0.000	0.001

[1] The first block reports the *Conversion Rate* (binary indicator equal to 1 if consumer makes at least one order during the experimental period). The second block reports *Cart Value*, expenditure per consumer conditional on making a purchase.
[2] Standard errors are in parentheses. % Change is calculated by dividing the treatment effect by the control group mean. *** p<0.01, ** p<0.05, * p<0.1.

Search Query Refinement Consumers arrive at e-commerce platforms with diverse needs. The search engine serves as the primary channel to facilitate consumers' discovery of desired products, allowing them to express preferences through search queries. Our focal platform seeks to accurately decode the latent demands behind consumers' multilingual queries, translate the queries, and retrieve products that align with their underlying needs. The effectiveness of this process is crucial

in determining match quality, which in turn impacts consumer purchase decisions and platform revenues. GenAI is well-positioned to improve the search algorithm's capabilities in translating consumer queries based on semantic understanding and refinement.

We conduct our analysis using the following regression model:

$$y_i = \beta \times Treat_i + \alpha_{cl(i)} + \epsilon_i, \tag{2}$$

where i denotes a consumer, y_i stands for a consumer's outcome variables, $Treat_i$ is an indicator of a consumer's treatment status. Consumers are classified into various cohorts based on their language groups and their first day of entry in the experiment. As multiple sub-experiments were conducted across consumers in different languages at varying dates, we include entry-day-by-language cohort fixed effects, $\alpha_{cl(i)}$.

The results are summarized in Table C3. Column 1 indicates no significant differences in product views between the two groups. However, treatment group consumers generated 1.1% more clicks (Column 2), spent 2.9% more (Column 4), and were 1.2% more likely to make a purchase (Column 5). We find no significant impact on cart value and order intensity (Columns 6 and 7).

We also explore further mechanism analysis of the Search Query Refinement application. In Table C4, we find that the likelihood of a product click increases by 0.3% ($p < 0.01$; Column 1), consistent with improved search performance in combination with the documented purchase conversion increase in our main effect. Columns 2 and 3 further indicate that treated consumers view fewer products prior to clicking or purchasing, suggesting a reduction in search intensity. In addition, we observe a statistically significant 2.0% increase in the click-through rate ($p < 0.01$; Column 4), defined as the ratio of product clicks to product views, suggesting that consumers found the exposed products more appealing and chose to seek additional details after viewing the summarized search results. The click-to-order conversion rate (Column 5), defined as the ratio of orders to clicks, remains statistically insignificant. This pattern echoes the fact that query refinement influenced only the composition of products retrieved immediately after a query search, not the information displayed on product detail pages. Overall, GenAI-facilitated query refinement enhanced the search algorithm's ability to satisfy consumers' demand, resulting in more effective matching and improved consumer purchases.

Product Description Well-crafted product descriptions are essential for informing consumers about product features, benefits, and uses, thereby reducing information asymmetry, facilitating consumer decision-making and driving platform sales. Despite its importance, our studied platform shows that nearly half of the self-sold products either lack a textual description or contain only a minimal description. GenAI's strengths in content recognition, comprehension, and generation can offer an effective solution to create comprehensive and structured product descriptions for a global

Table C3: Main Effect of Search Query Refinement

	(1) Views	(2) Clicks	(3) Orders	(4) Sales	(5) Conversion Rate	(6) Cart Value	(7) Order Intensity
Treat	-0.549	0.0901***	0.00154	0.0648**	0.00101**	0.370	-0.00315
	(0.887)	(0.0245)	(0.00107)	(0.0314)	(0.000411)	(0.334)	(0.00842)
%Change	-0.18%	1.10%	0.94%	2.93%	1.15%	1.47%	-0.17%
Observations	1,849,382	1,849,382	1,849,382	1,849,382	1,849,382	163,381	163,381
R-squared	0.038	0.041	0.019	0.004	0.030	0.010	0.004

[1] "Views" stands for the number of product views in the summarized search results pages. "Clicks" stands for the number of product clicks into product detail pages. "Orders" is the number of product orders. "Sales" represents the total expenditure on product orders. "Conversion Rate" measures consumers' likelihood of making purchases. It is a binary indicator for purchase, which equals 1 if a consumer makes at least one order during the experimental period, and 0 otherwise. "Cart Value" refers to the expenditure per consumer, conditional on making a purchase. "Order Intensity" refers to the number of orders per consumer, conditional on making a purchase.

[2] Standard errors are in parentheses. % Change is calculated by dividing the treatment effect by the control group mean. *** p<0.01, ** p<0.05, * p<0.1.

Table C4: More Exploration of Search Query Refinement

	(1) Is Click	(2) Views Conditional on Click	(3) Views Conditional Order	(4) Click-through Rate	(5) Click-to-Order Conversion Rate
Treat	0.00267***	-1.728*	-10.34*	0.000767***	-0.000088
	(0.00057)	(1.034)	(5.362)	(0.000079)	(0.000182)
%Change	0.33%	-0.46%	-1.48%	2.02%	-0.35%
Observations	1,849,382	1,508,873	163,381	1,849,382	1,508,873
R-squared	0.013	0.039	0.069	0.003	0.014

[1] "Is Click" measures consumers' likelihood of making a click. It is a binary indicator for click, which equals 1 if a consumer makes at least one click during the experimental period, and 0 otherwise. "Views Conditional on Click" refers to the product views per consumer, conditional on making a click. "Views Conditional on Order" refers to the product views per consumer, conditional on making a purchase. "Click-through Rate" is the ratio of the number of product clicks to the number of product views, measuring the degree of conversion from views to clicks. "Click-to-Order Conversion Rate" stands for the ratio of the number of product orders to the number of product clicks, measuring the degree of conversion from clicks to purchases.

[2] Standard errors are in parentheses. % Change is calculated by dividing the treatment effect by the control group mean. *** p<0.01, ** p<0.05, * p<0.1.

audience.

We conduct our analysis using the following regression model:

$$y_i = \beta \times Treat_i + \alpha_{cl(i)} + \epsilon_i, \tag{3}$$

where i denotes a consumer, y_i stands for a consumer's outcome variables, $Treat_i$ is an indicator for whether the consumer is assigned to the treatment group. Because multiple sub-experiments were implemented across language groups on different start dates, we include entry-day-by-language cohort fixed effects, $\alpha_{cl(i)}$.

Column 1 of Table C5 shows no statistically significant differences in product clicks between the control and treatment groups. However, conditional on consumers clicking through to product detail pages—where the descriptions are displayed—treated consumers place 1.1% more orders and spend 2.1% more on those orders (Columns 2 and 3). This improvement is also reflected in a 1.3% increase in the conversion rate (Column 4), indicating a higher likelihood of purchase following exposure to AI-generated descriptions. By contrast, we detect no statistically significant changes in cart value or order intensity. Taken together, these results suggest that augmenting human-generated product descriptions with AI-generated content primarily affects purchase incidence rather than spending intensity, leading to higher overall sales.

Moreover, we stratify products based on the length of their original, human-generated descriptions, distinguishing between those with no or insufficient text (fewer than 50 words) and those with sufficiently detailed descriptions (more than 50 words). Products in the former group experience a 6.5% increase in sales following augmentation with AI-generated content ($p < 0.05$), whereas products in the latter group show no significant effect (Columns 1 and 2 of Table C6), indicating that richer descriptions facilitate consumer decision-making.[1]

Marketing Push Message The platform leverages marketing push notifications, direct messages sent to consumers via their platform app, to draw traffic and boost transactions. Because creating a large volume of diverse and targeted marketing messages manually was challenging, the number of marketing messages is far smaller than the hundreds of millions of consumers, often resulting in many consumers receiving identical content. With the introduction of GenAI, the platform can produce millions of distinct messages, enabling highly personalized marketing strategies through push notifications.

[1]Based on internal research and expert surveys conducted by our partner platform, descriptions containing fewer than 50 words are classified as providing insufficient textual information. This analysis is restricted to the English-language sub-experiment, as description-length data are available only for English-language content.

Table C5: Main Effect of Product Description

	(1) Clicks	(2) Orders	(3) Sales	(4) Conversion Rate	(5) Cart Value	(6) Order Intensity
Treat	0.00233	0.000600**	0.0104**	0.000554***	0.0944	-0.00186
	(0.00183)	(0.000278)	(0.00417)	(0.000187)	(0.0805)	(0.00320)
%Change	0.12%	1.08%	2.05%	1.27%	0.82%	-0.15%
Observations	4,772,937	4,772,937	4,772,937	4,772,937	210,155	210,155
R-squared	0.055	0.008	0.002	0.008	0.010	0.021

[1] "Clicks" stands for the number of product clicks into product detail pages. "Orders" is the number of product orders. "Sales" represents the total expenditure on product orders. "Conversion Rate" measures consumers' likelihood of making purchases. It is a binary indicator for purchase, which equals 1 if a consumer makes at least one order during the experimental period, and 0 otherwise. "Cart Value" refers to the expenditure per consumer, conditional on making a purchase. "Order Intensity" refers to the number of orders per consumer, conditional on making a purchase.
[2] Standard errors are in parentheses. % Change is calculated by dividing the treatment effect by the control group mean. *** p<0.01, ** p<0.05, * p<0.1.

Table C6: Product Description: Heterogeneity by Length of Original, Human-generated Description

	(1) Sales ≤50 words	(2) Sales >50 words	(3) Conversion Rate ≤50 words	(4) Conversion Rate >50 words	(5) Cart Value ≤50 words	(6) Cart Value >50 words
Treat	0.0115**	0.0001	0.00047**	0.00044*	0.367	-0.188
	(0.0050)	(0.0064)	(0.00022)	(0.00026)	(0.235)	(0.198)
%Change	6.50%	0.03%	2.43%	1.60%	3.99%	-1.50%
P-value	0.0536		0.5490		0.0653	
Observations	1,628,409	1,628,409	1,628,409	1,628,409	31,759	45,500
R-squared	0.000	0.001	0.003	0.005	0.001	0.004

[1] "Sales" represents the total expenditure on product orders. "Conversion Rate" measures consumers' likelihood of making purchases. It is a binary indicator for purchase, which equals 1 if a consumer makes at least one order during the experimental period, and 0 otherwise. "Cart Value" refers to the expenditure per consumer, conditional on making a purchase.
[2] "≤50 words" refers to descriptions containing fewer than 50 words, while ">50 words" refers to descriptions containing more than 50 words.
[3] Standard errors are in parentheses. % Change is calculated by dividing the treatment effect by the control group mean. The p-values are from seemingly unrelated estimations testing the equality of % treatment effects across the two groups. *** p<0.01, ** p<0.05, * p<0.1.

We conduct our analysis using the following regression model:

$$y_i = \alpha + \beta \times Treat_i + \epsilon_i \tag{4}$$

where i denotes a consumer, y_i stands for a consumer's outcome variables, $Treat_i$ is an indicator for whether the consumer is assigned to the treatment group.

Table C7 shows that the use of AI-generated marketing messages leads to increases in consumer engagement. Specifically, clicks increase by 3.1%, orders by 2.8%, and the point estimate for total

purchase amount increases by 1.6%, though it is not statistically significant (Columns 1–3). In addition, the probability that a consumer makes a purchase rises by 3%, while cart value and order intensity remain statistically unchanged (Columns 4–6). Taken together, these results suggest that GenAI enhances the effectiveness of marketing content primarily by expanding consumer participation, consistent with its ability to unlock personalization at scale in settings where human-generated content is constrained by limited resources.

Table C7: Main Effect of Marketing Push

	(1) Clicks	(2) Orders	(3) Sales	(4) Conversion Rate	(5) Cart Value	(6) Order Intensity
Treat	0.000529***	0.000052*	0.000402	0.000048**	-0.206	-0.00138
	(0.000071)	(0.000028)	(0.000816)	(0.0000218)	(0.454)	(0.00854)
%Change	3.08%	2.83%	1.60%	2.95%	-1.32%	-0.12%
Observations	13,715,528	13,715,528	13,715,528	13,715,528	22,425	22,425
R-squared	0.000	0.000	0.000	0.000	0.000	0.000

[1] "Clicks" stands for the number of clicks on the marketing messages. "Orders" is the number of product orders. "Sales" represents the total expenditure on product orders. "Conversion Rate" measures consumers' likelihood of making purchases. It is a binary indicator for purchase, which equals 1 if a consumer makes at least one order during the experimental period, and 0 otherwise. "Cart Value" refers to the expenditure per consumer, conditional on making a purchase. "Order Intensity" refers to the number of orders per consumer, conditional on making a purchase.

[2] Standard errors are in parentheses. % Change is calculated by dividing the treatment effect by the control group mean. *** p<0.01, ** p<0.05, * p<0.1.

Google Advertising Title The platform buys advertising slots in the sponsored section of Google Shopping to promote its products on Google and attract traffic to its site. To maximize purchases derived from Google advertisements, a critical operational decision for the platform is how to design product titles to increase both product discoverability and the likelihood of user clicks. The platform leveraged GenAI to refine titles based on the original seller-created titles, optimizing them for better visibility and engagement.

We conduct our analysis employing the following regression model:

$$y_i = \beta \times Treat_i + \alpha_{c(i)} + \epsilon_i, \tag{5}$$

where i denotes a product, y_i stands for the outcome variables for a product, $Treat_i$ is an indicator for whether the product is assigned to the treatment group. We control for product entry-day cohort fixed effect $\alpha_{c(i)}$.

Table C8 presents the main findings. Columns 1 and 2 indicate a 7.7% decrease in ad views and a 10.3% decrease in ad clicks for the treatment group, respectively. Columns 3, 4, and 5 report a non-significant reduction in sales, conversion rate, and cart value, respectively. As we discussed in

Section 3.1 of the main paper, the null effect on sales can be attributed to the lack of fine-tuning using e-commerce domain knowledge when setting up the GenAI model.

Table C8: Main Effect of Google Advertising

	(1) Views	(2) Clicks	(3) Sales	(4) Conversion Rate	(5) Cart Value
Treat	-1.547***	-0.0247***	-0.00602	-0.000090	-0.784
	(0.148)	(0.00304)	(0.00534)	(0.000111)	(0.992)
%Change	-7.68%	-10.26%	-4.56%	-2.29%	-2.32%
Observations	1,244,016	1,244,016	1,244,016	1,244,016	4,811
R-squared	0.000	0.000	0.000	0.000	0.000

[1] "Views" represents the number of times the product advertisement is viewed on Google. "Clicks" refers to the number of times the product advertisement is clicked on Google. "Sales" represents the total expenditure on product orders. "Conversion Rate" is 1 if a product is purchased at least once during the experiment period, and 0 otherwise. "Cart Value" refers to the expenditure per product, conditional on the product being purchased.

[2] Standard errors are in parentheses. % Change is calculated by dividing the treatment effect by the control group mean. *** p<0.01, ** p<0.05, * p<0.1.

Chargeback Defense Online sellers often struggle to defend against chargebacks due to reasons such as non-receipt of goods. Chargebacks can lead to significant financial losses and jeopardize the long-term sustainability of sellers' businesses on the platform. The whole process of contesting chargeback disputes includes analyzing claims, collecting necessary evidence (e.g., order details, fulfillment records, proof of shipment and logistics tracking through ways like interfacing with diverse APIs), and crafting compelling chargeback defense letters. The rapid advancement of GenAI enabled the platform to develop a chargeback defense agent that offers a one-stop solution to streamline the intricacies of chargeback disputes.

As the data was not available for us to review, we report findings estimated by the platform's internal data science team. Their estimates indicate that the adoption of the GenAI agent helps increase the success rate of chargeback defense by 15%.

Live Chat Translation E-commerce platforms must provide robust consumer services for consumers seeking consultation or negotiation with the platform, such as addressing inquiries about the platform's promotional details and resolving disputes when consensus with sellers is not reached. For our focal platform, delivering native-language consumer services to a diverse, multilingual consumer base incurs significant costs. Thus, a significant portion of non-English consumer inquiries were supported by Filipino consumer service agents in English. A straightforward application of GenAI allows the platform to equip low-cost Filipino agents with robust real-time translation support, aiming to provide more effective communication between consumers and agents.

Similarly, due to the unavailability of raw data, the effect estimate for this process is from the platform's internal data science team and could not be independently verified. During the experiment, consumers were queried whether they were satisfied or not with the service via a survey question immediately after service completion. As a result, there was a 5.2% increase in consumer satisfaction, suggesting that GenAI helped Filipino agents to better serve non-English-speaking consumers.

Post-purchase Outcomes In Table C9, we provide evidence on two important post-purchase measures of consumer satisfaction with the products, namely product return rates and customer ratings. We do not find evidence that GenAI applications deteriorate such outcomes.

Table C9: Average Treatment Effects of GenAI Adoption on Product Returns and Reviews

	Product Return Rate			Positive Review Rate		
	(1)	(2)	(3)	(4)	(5)	(6)
Business Workflow	Coefficient	% Change	Obs	Coefficient	% Change	Obs
Pre-sale Service Chatbot	0.0208	2.08%	3,076	0.0452*	4.52%	1,008
	(0.0582)			(0.0247)		
Search Query Refinement	-0.0141	-1.41%	163,381	0.0031	0.31%	26,209
	(0.0152)			(0.0040)		
Product Description	-0.0386***	-3.86%	210,155	-0.0042	-0.42%	31,916
	(0.0142)			(0.0034)		
Marketing Push Message	-0.114***	-11.40%	22,425	-0.0174	-1.74%	2,853
	(0.0394)			(0.0122)		

[1] "Return Rate" is defined as the share of orders that are returned within a year after the purchase. "Positive Review Rate" is defined as the share of rated orders that receive four- or five-star ratings on a five-point scale. The estimation of Return Rate is conditional on consumers with orders, while the estimation of Positive Review Rate is conditional on consumers with rated orders. Such data are not available for the Google Advertising Title workflow. To protect proprietary business information, both outcome variables are normalized by the control-group mean. Consequently, coefficients can be interpreted as percentage changes relative to the control condition.

[2] Columns (1) and (4) report the estimated coefficients, with standard errors in parentheses. Columns (2) and (5) report % Change, calculated as the treatment effect divided by the control group mean. Columns (3) and (6) report the number of observations. *** p<0.01, ** p<0.05, * p<0.1.

D Details on Consumer Treatment Effect Heterogeneity

Pre-sale Service Chatbot In this experiment, we focus on the comparison between consumers who are served only by the GenAI chatbot and those who are served by an auto-response indicating service unavailability. Table D1 reports the heterogeneous treatment effects across consumer groups. Our analysis reveals that the gains in sales are more pronounced among newer consumers with shorter registration histories (Column 2), less active consumers with fewer login days (Column 4), and consumers with less past spending (Column 6). However, differences across consumer groups are generally not statistically significant, with the exception of sales across past purchases, for which the difference is significant at the 10% level.

Search Query Refinement Table D2 reports the heterogeneous treatment effect of refining search query with GenAI on different consumer groups. For sales, the benefits are significant and larger for inexperienced consumers (Columns 2, 4, and 6), while the effects for more experienced consumers are smaller and insignificant (Columns 1, 3, and 5). The differences between these two consumer groups are statistically significant when consumers are classified by past purchases and past login days. When focusing on conversion rates, we also find statistically significant differences between consumer groups defined by years since registration. Since consumers with limited online experience often struggle to effectively articulate their needs through query-based searches, they tend to benefit more from enhanced match quality achieved by applying GenAI to the semantic translation of consumer queries.

Product Description In Table D3, we observe a similar pattern to Search Query Refinement. There is a significant and more pronounced sales increase for inexperienced consumers (Columns 2, 4, and 6). The differences between high- and low-group consumers are statistically significant for consumers classified by past purchases and past login days. Augmenting product descriptions with AI-generated content substantially enhances the sufficiency and clarity of product information, thereby motivating consumer purchase decisions, particularly among less experienced consumers.

Marketing Push Message In Table D4, we find that the effects of AI-generated marketing push messages are concentrated among consumers with fewer past purchases. For this group, treatment significantly increases both sales and conversion rates (Column 6), while the corresponding estimates for high-purchase consumers are negative and statistically insignificant (Column 5); the high-low differences are statistically significant. For registered years and past login days, conversion-rate gains are larger for lower-experience consumers, but the differences across groups are not statistically significant. These patterns suggest that AI-generated push messages are particularly effective for consumers with less purchase history, likely by making promotional content more relevant or salient.

Table D1: Consumer HTE for Pre-sale Service Chatbot

	(1)	(2)	(3)	(4)	(5)	(6)
	Registered Years		Past Login Days		Past Purchases	
	High	Low	High	Low	High	Low
Panel A: Sales						
Treat	0.217	0.329***	0.318**	0.230**	0.159	0.343***
	(0.153)	(0.118)	(0.156)	(0.114)	(0.180)	(0.105)
%Change	10.38%	25.76%	15.00%	18.54%	6.82%	27.79%
P-value	0.1683		0.7520		0.0606	
Panel B: Conversion Rate						
Treat	0.0131***	0.0131***	0.0128***	0.0135***	0.0128***	0.0130***
	(0.00377)	(0.00333)	(0.00386)	(0.00321)	(0.00434)	(0.00300)
%Change	18.77%	25.77%	17.11%	29.62%	16.41%	27.09%
P-value	0.4000		0.1212		0.1955	
Panel C: Cart Value						
Treat	-2.130	0.0141	-0.516	-2.331	-2.470	0.157
	(1.432)	(1.471)	(1.387)	(1.525)	(1.568)	(1.320)
% Change	-7.11%	0.06%	-1.82%	-8.56%	-8.27%	0.61%
P-value	0.3257		0.3702		0.2170	
Observation (Panel A&B)	22,461	22,153	22,570	22,044	18,610	26,004
Observation (Panel C)	1,761	1,315	1,877	1,199	1,609	1,467

[1] We classify consumers into high and low groups and capture their online shopping experience based on registration duration, 30-day pre-experiment login days and 30-day pre-experiment purchase. For each indicator, consumers in the low group are defined as relatively inexperienced if they fall below the median of the corresponding distribution.

[2] "Sales" represents the total expenditure on product orders. "Conversion Rate" measures consumers' likelihood of making purchases. It is a binary indicator for purchase, which equals 1 if a consumer makes at least one order during the experimental period, and 0 otherwise. "Cart Value" refers to the expenditure per consumer, conditional on making a purchase.

[3] Standard errors are in parentheses. % Change is calculated by dividing the treatment effect by the control group mean. *** p<0.01, ** p<0.05, * p<0.1.

Table D2: Consumer HTE for Search Query Refinement

	(1)	(2)	(3)	(4)	(5)	(6)
	Registered Years		Past Login Days		Past Purchases	
	High	Low	High	Low	High	Low
Panel A: Sales						
Treat	0.0360	0.0867**	0.0203	0.104***	-0.0216	0.106***
	(0.0526)	(0.0380)	(0.0566)	(0.0303)	(0.0757)	(0.0291)
%Change	1.27%	5.01%	0.63%	8.16%	-0.56%	7.46%
P-value	0.2137		0.0036		0.0047	
Panel B: Conversion Rate						
Treat	-0.000104	0.00186***	0.000500	0.00141***	0.000651	0.00115***
	(0.000697)	(0.000487)	(0.000675)	(0.000482)	(0.000907)	(0.000421)
%Change	-0.09%	2.79%	0.43%	2.32%	0.44%	1.93%
P-value	0.0023		0.0421		0.1122	
Panel C: Cart Value						
Treat	0.329	0.440	-0.0145	1.126**	-0.355	1.224***
	(0.431)	(0.526)	(0.452)	(0.460)	(0.484)	(0.450)
%Change	1.34%	1.69%	-0.05%	5.36%	-1.35%	5.13%
P-value	0.8965		0.0363		0.0139	
Observation (Panel A&B)	813,317	1,036,065	890,044	959,338	596,721	1,252,661
Observation (Panel C)	93,362	70,019	104,531	58,850	88,135	75,246

[1] Refer to Table D1 for detailed notes.

Table D3: Consumer HTE for Product Description

	(1)	(2)	(3)	(4)	(5)	(6)
	Registered Years		Past Login Days		Past Purchases	
	High	Low	High	Low	High	Low
Panel A: Sales						
Treat	0.00671	0.0130***	-0.00606	0.0263***	0.000224	0.0206***
	(0.00761)	(0.00455)	(0.00655)	(0.00522)	(0.00718)	(0.00423)
%Change	1.09%	3.06%	-1.02%	6.24%	0.03%	5.63%
P-value	0.2525		0.0001		0.0005	
Panel B: Conversion Rate						
Treat	0.000575*	0.000520**	0.000325	0.000785***	0.000568*	0.000533**
	(0.000312)	(0.000229)	(0.000284)	(0.000245)	(0.000292)	(0.000233)
%Change	1.10%	1.39%	0.65%	2.06%	1.05%	1.59%
P-value	0.7441		0.1194		0.5235	
Panel C: Cart Value						
Treat	0.003	0.184*	-0.180	0.438***	-0.127	0.447***
	(0.126)	(0.098)	(0.112)	(0.115)	(0.115)	(0.098)
%Change	0.03%	1.62%	-1.50%	3.96%	-1.06%	4.09%
P-value	0.2496		0.0001		0.0001	
Observation (Panel A&B)	2,035,278	2,737,659	2,322,437	2,450,500	2,386,336	2,386,601
Observation (Panel C)	107,098	103,057	115,708	94,447	129,462	80,693

[1] Refer to Table D1 for detailed notes.

Table D4: Consumer HTE for Marketing Push Message

	(1)	(2)	(3)	(4)	(5)	(6)
	Registered Years		Past Login Days		Past Purchases	
	High	Low	High	Low	High	Low
Panel A: Sales						
Treat	-0.000269	0.00128	0.000694	0.000195	-0.00250	0.00238***
	(0.00115)	(0.00112)	(0.00136)	(0.00100)	(0.00161)	(0.000712)
% Change	-0.91%	6.63%	2.47%	0.85%	-5.88%	20.64%
P-value	0.4519		0.8605		0.0003	
Panel B: Conversion Rate						
Treat	0.0000314	0.0000681**	0.0000122	0.0000737***	-0.0000590	0.000111***
	(0.0000301)	(0.0000312)	(0.0000345)	(0.0000281)	(0.0000416)	(0.0000210)
% Change	1.76%	4.98%	0.71%	4.82%	-2.22%	14.17%
P-value	0.4372		0.2810		0.0000	
Panel C: Cart Value						
Treat	-0.432	0.225	0.285	-0.573	-0.600	0.828
	(0.578)	(0.731)	(0.714)	(0.583)	(0.558)	(0.761)
% Change	-2.62%	1.60%	1.75%	-3.80%	-3.76%	5.62%
P-value	0.4956		0.3551		0.1286	
Observations (Panel A&B)	7,959,851	5,755,677	5,796,995	7,918,533	6,085,076	7,630,452
Observations (Panel C)	14,351	8,074	10,026	12,399	16,025	6,400

[1] Refer to Table D1 for detailed notes.

E Details on Seller Treatment Effect Heterogeneity

Search Query Refinement Table E1 reports the heterogeneous impact on high- versus low-type sellers classified based on three metrics: annual past sales, tenure on the platform, and number of sub-accounts. Small sellers with lower transaction volumes (Column 2), shorter operational histories (Column 4), and fewer sub-accounts (Column 6) experience a significant and larger increase in sales from treated consumers. By contrast, sales on larger, tenured, and scaled sellers show no significant change. The differences between these two seller groups are statistically significant when sellers are divided by operation years and the number of sub-accounts. When using conversion rates, we also find statistically significant differences between seller groups defined by annual sales. Thus, the GenAI-powered search query refinement generates greater value for smaller sellers.

Marketing Push Message In Table E2, we find limited evidence of heterogeneity across seller groups. Most high-low differences are statistically insignificant across sales, conversion rates, and cart values. The main exception is conversion rates by the number of sub-accounts: sellers with fewer sub-accounts experience a larger conversion-rate gain, and the high-low difference is marginally significant at the 10% level.

Google Advertising Title Table E3 shows that the differences between high- and low-group sellers are all statistically insignificant.

Table E1: Seller HTE for Search Query Refinement

	(1)	(2)	(3)	(4)	(5)	(6)
	Annual Sales		Operation Years		# of Sub-Accounts	
	High	Low	High	Low	High	Low
Panel A: Sales						
Treat	0.0241	0.0407**	0.0070	0.0578**	0.00238	0.0624**
	(0.0243)	(0.0180)	(0.0182)	(0.0237)	(0.0174)	(0.0246)
%Change	2.18%	3.68%	0.62%	5.38%	0.24%	5.19%
P-value	0.5661		0.0652		0.0516	
Panel B: Conversion Rate						
Treat	0.000085	0.00105***	0.000444	0.000673**	0.000242	0.00100***
	(0.000291)	(0.000352)	(0.000343)	(0.000306)	(0.000317)	(0.000330)
%Change	0.21%	1.69%	0.76%	1.47%	0.49%	1.85%
P-value	0.0573		0.3493		0.0738	
Panel C: Cart Value						
Treat	0.550	0.238	-0.042	0.773	-0.054	0.613
	(0.554)	(0.267)	(0.287)	(0.486)	(0.325)	(0.426)
%Change	2.06%	1.34%	-0.22%	3.29%	-0.26%	2.75%
P-value	0.7711		0.1484		0.2069	
Observation (Panel A&B)	1,849,382	1,849,382	1,849,382	1,849,382	1,849,382	1,849,382
Observation (Panel C)	76,536	115,804	108,790	85,195	91,774	100,643

[1] We classify sellers into high and low groups based on three different proxies. Low-group sellers are generally small sellers, as defined by meeting the following pre-experiment criteria: (1) accounting for the bottom 50% cumulative share of total sales; (2) having operated on the platform for fewer than five years; or (3) maintaining fewer than three sub-accounts for their online store. Platform-operated sellers are classified as large.

[2] "Sales" represents the total expenditure on product orders. "Conversion Rate" measures consumers' likelihood of making purchases. It is a binary indicator for purchase, which equals 1 if a consumer makes at least one order during the experimental period, and 0 otherwise. "Cart Value" refers to the expenditure per consumer, conditional on making a purchase.

[3] Standard errors are in parentheses. % Change is calculated by dividing the treatment effect by the control group mean. *** p<0.01, ** p<0.05, * p<0.1.

Table E2: Seller HTE for Marketing Push Message

	(1)	(2)	(3)	(4)	(5)	(6)
	Annual Seller Sales		Operation Years		# of Sub-Accounts	
	High	Low	High	Low	High	Low
Panel A: Sales						
Treat	0.000216	0.000186	0.000453	-0.0000514	-0.0000206	0.000422
	(0.000594)	(0.000559)	(0.000579)	(0.000575)	(0.000517)	(0.000631)
% Change	1.84%	1.38%	3.31%	-0.45%	-0.18%	3.14%
P-value	0.9436		0.5660		0.6060	
Panel B: Conversion Rate						
Treat	0.0000240	0.0000236	0.0000166	0.0000310**	0.00000409	0.0000435***
	(0.0000147)	(0.0000161)	(0.0000170)	(0.0000137)	(0.0000157)	(0.0000152)
% Change	3.28%	2.69%	1.68%	4.97%	0.48%	5.68%
P-value	0.8299		0.2370		0.0557	
Panel C: Cart Value						
Treat	-0.221	-0.195	0.223	-0.951	-0.0912	-0.420
	(0.734)	(0.564)	(0.530)	(0.813)	(0.553)	(0.729)
% Change	-1.38%	-1.27%	1.61%	-5.16%	-0.66%	-2.40%
P-value	0.9852		0.2488		0.7633	
Observation (Panel A&B)	13,715,528	13,715,528	13,715,528	13,715,528	13,715,528	13,715,528
Observation (Panel C)	10,212	12,213	13,649	8,776	11,618	10,807

[1] Refer to Table E1 for detailed notes.

Table E3: Seller HTE for Google Advertising Title

	(1)	(2)	(3)	(4)	(5)	(6)
	Annual Seller Sales		Operation Years		# of Sub-Accounts	
	High	Low	High	Low	High	Low
Panel A: Sales						
Treat	-0.00605	-0.00610	-0.00656	-0.00578	-0.00759	-0.00562
	(0.00711)	(0.00797)	(0.00935)	(0.00650)	(0.0125)	(0.00589)
% Change	-4.97%	-4.27%	-5.23%	-4.27%	-5.54%	-4.29%
P-value	0.9301		0.9099		0.9029	
Panel B: Conversion Rate						
Treat	-0.000186	0.0000057	-0.0000884	-0.0000906	-0.0000464	-0.000100
	(0.000155)	(0.000159)	(0.000189)	(0.000137)	(0.000232)	(0.000127)
% Change	-4.82%	0.14%	-2.46%	-2.23%	-1.33%	-2.49%
P-value	0.4048		0.9713		0.8736	
Panel C: Cart Value						
Treat	-0.0528	-1.588	-0.990	-0.697	-1.672	-0.602
	(1.372)	(1.425)	(1.896)	(1.162)	(2.520)	(1.071)
% Change	-0.17%	-4.41%	-2.84%	-2.09%	-4.27%	-1.85%
P-value	0.4551		0.9014		0.7378	
Observations (Panel A&B)	622,083	621,933	397,339	846,677	258,157	985,859
Observation (Panel C)	2,343	2,468	1,411	3,400	897	3,914

[1] Refer to Table E1 for detailed notes.

F Details on Product Treatment Effect Heterogeneity

Pre-sale Service Chatbot Table F1 reports the product-level heterogeneous treatment effects of the Pre-sale Service Chatbot experiment. When focusing on conversion rates, we detect statistically significant differences between product groups classified by annual sales quantity, indicating that the GenAI-driven chatbot service is more effective at converting consumers for tail products.

Search Query Refinement In Table F2, we find that for sales, the gains are larger and statistically significant only for products in low-concentration categories (Column 2), products with lower sales volume (Column 4), and products with high price level (Column 5). The differences between these two product groups are statistically significant when products are classified by market concentration and annual quantity, indicating that GenAI reduces search frictions in settings with greater product differentiation or limited sales history.

Product Description Table F3 shows that, for sales, statistically significant differences across product groups arise only when products are classified by price level. This pattern is consistent with GenAI being more effective at reducing information asymmetries in settings with higher decision stakes.

Google Advertising Title Table F5 shows no statistically significant differences between the two product groups.

Marketing Push Message Table F4 shows that, in most cases, we do not observe statistically significant differences between the two product groups.

Table F1: Product HTE for Pre-sale Service Chatbot

	(1)	(2)	(3)	(4)	(5)	(6)
	Market Concentration		Annual Quantity		Price	
	High	Low	High	Low	High	Low
Panel A: Sales						
Treat	0.136**	0.138*	0.0597	0.214***	0.137*	0.137**
	(0.0532)	(0.0821)	(0.0564)	(0.0799)	(0.0782)	(0.0589)
% Change	21.28%	13.18%	8.77%	21.28%	16.61%	15.91%
P-value	0.4724		0.2696		0.9564	
Panel B: Conversion Rate						
Treat	0.00647***	0.00666***	0.00265	0.0105***	0.00404**	0.00910***
	(0.00166)	(0.00196)	(0.00162)	(0.00198)	(0.00158)	(0.00202)
% Change	26.60%	18.48%	10.32%	30.28%	17.44%	24.46%
P-value	0.3443		0.0182		0.4139	
Panel C: Cart Value						
Treat	-1.108	-1.300	-0.366	-1.990	-0.258	-1.584*
	(1.182)	(1.551)	(1.370)	(1.472)	(2.182)	(0.926)
% Change	-4.22%	-4.47%	-1.38%	-6.86%	-0.72%	-6.84%
P-value	0.9704		0.4498		0.3981	
Observation (Panel A&B)	44,614	44,614	44,614	44,614	44,614	44,614
Observation (Panel C)	1,274	1,802	1,223	1,853	1,151	1,925

[1] We classify products into high and low groups based on three key pre-experiment dimensions. (1) Category market concentration, measured by the sales share of the top 1% of products (ranked by annual sales) within each category. Products in the low group belong to categories with concentration levels below the platform average. (2) Annual sales quantity, also defined within the category. Products in the low group—referred to as tail products—are those comprising the bottom 50% cumulative share of total sales quantity within each category. (3) Product price, defined within each category to control for category-level pricing variation. Low-priced products are those priced below the median of their respective category.

[2] "Sales" represents the total expenditure on product orders. "Conversion Rate" measures consumers' likelihood of making purchases. It is a binary indicator for purchase, which equals 1 if a consumer makes at least one order during the experimental period, and 0 otherwise. "Cart Value" refers to the expenditure per consumer, conditional on making a purchase.

[3] Standard errors are in parentheses. % Change is calculated by dividing the treatment effect by the control group mean. *** p<0.01, ** p<0.05, * p<0.1.

Table F2: Product HTE for Search Query Refinement

	(1)	(2)	(3)	(4)	(5)	(6)
	Market Concentration		Annual Quantity		Price	
	High	Low	High	Low	High	Low
Panel A: Sales						
Treat	-0.00862	0.0734***	-0.00381	0.0686***	0.0590**	0.00586
	(0.0174)	(0.0253)	(0.0156)	(0.0258)	(0.0296)	(0.00864)
% Change	-0.80%	6.49%	-0.47%	4.92%	3.79%	0.89%
P-value	0.0067		0.0332		0.1937	
Panel B: Conversion Rate						
Treat	0.000247	0.000823***	0.0000005	0.00121***	0.000526*	0.000548
	(0.000332)	(0.000302)	(0.000305)	(0.000343)	(0.000301)	(0.000342)
% Change	0.45%	1.85%	0.00%	2.07%	1.19%	0.94%
P-value	0.0888		0.0064		0.7493	
Panel C: Cart Value						
Treat	-0.292	1.106**	-0.098	0.587	0.717	-0.032
	(0.291)	(0.534)	(0.319)	(0.411)	(0.615)	(0.132)
%Change	-1.49%	4.35%	-0.55%	2.46%	2.04%	-0.28%
P-value	0.0208		0.2052		0.2583	
Observations (Panel A&B)	1,849,382	1,849,382	1,849,382	1,849,382	1,849,382	1,849,382
Observation (Panel C)	101,975	82,912	84,799	109,265	82,272	108,485

[1] Refer to Table F1 for detailed notes.

Table F3: Product HTE for Product Description

	(1)	(2)	(3)	(4)	(5)	(6)
	Market Concentration		Annual Quantity		Price	
	High	Low	High	Low	High	Low
Panel A: Sales						
Treat	0.00932***	0.00113	0.00497*	0.00547*	0.00760***	0.00285
	(0.00299)	(0.00284)	(0.00281)	(0.00299)	(0.00291)	(0.00286)
% Change	3.10%	0.55%	2.10%	2.03%	4.10%	0.89%
P-value	0.1309		0.9641		0.0703	
Panel B: Conversion Rate						
Treat	0.000384**	0.000141	0.000456***	0.000166	0.000393***	0.000209
	(0.000151)	(0.000120)	(0.000134)	(0.000141)	(0.000100)	(0.000164)
% Change	1.38%	0.81%	2.07%	0.69%	3.32%	0.63%
P-value	0.5014		0.0845		0.0047	
Panel C: Cart Value						
Treat	0.186**	-0.019	0.018	0.138	0.092	0.032
	(0.089)	(0.141)	(0.108)	(0.104)	(0.204)	(0.071)
%Change	1.72%	-0.16%	0.16%	1.24%	0.59%	0.33%
P-value	0.1895		0.4258		0.8605	
Observations (Panel A&B)	4,772,937	4,772,937	4,772,937	4,772,937	4,772,937	4,772,937
Observation (Panel C)	133,779	83,687	106,252	115,810	57,458	159,492

[1] Refer to Table F1 for detailed notes.

Table F4: Product HTE for Marketing Push Message

	(1)	(2)	(3)	(4)	(5)	(6)
	Market Concentration		Annual Quantity		Price	
	High	Low	High	Low	High	Low
Panel A: Sales						
Treat	0.000146	0.000255	-0.0000554	0.000457	-0.000429	0.000831
	(0.000339)	(0.000742)	(0.000349)	(0.000737)	(0.000511)	(0.000636)
% Change	3.03%	1.25%	-0.92%	2.39%	-5.21%	4.90%
P-value	0.8225		0.6347		0.1631	
Panel B: Conversion Rate						
Treat	0.0000213**	0.0000263	0.0000115	0.0000361*	0.0000130	0.0000346*
	(0.00000921)	(0.0000198)	(0.0000108)	(0.0000190)	(0.00000976)	(0.0000195)
% Change	7.59%	1.98%	2.91%	2.97%	4.06%	2.68%
P-value	0.1190		0.9813		0.6838	
Panel C: Cart Value						
Treat	-0.730	-0.108	-0.566	-0.0896	-2.292*	0.285
	(1.038)	(0.504)	(0.772)	(0.546)	(1.381)	(0.444)
% Change	-4.24%	-0.71%	-3.71%	-0.57%	-8.92%	2.17%
P-value	0.6095		0.6106		0.0825	
Observations (Panel A&B)	13,715,528	13,715,528	13,715,528	13,715,528	13,715,528	13,715,528
Observations (Panel C)	3,993	18,432	5,498	16,927	4,483	17,942

[1] Refer to Table F1 for detailed notes.

Table F5: Product HTE for Google Advertising Title

	(1)	(2)	(3)	(4)	(5)	(6)
	Market Concentration		Annual Quantity		Price	
	High	Low	High	Low	High	Low
Panel A: Sales						
Treat	-0.00564	-0.00651	-0.00247	-0.0109	-0.00831	-0.00282
	(0.00709)	(0.00811)	(0.00736)	(0.00766)	(0.00758)	(0.00727)
% Change	-4.16%	-5.10%	-1.71%	-9.39%	-5.98%	-2.30%
P-value	0.9073		0.3350		0.6386	
Panel B: Conversion Rate						
Treat	-0.0000708	-0.000113	-0.0000432	-0.000154	-0.0000788	-0.000116
	(0.000151)	(0.000165)	(0.000156)	(0.000155)	(0.000135)	(0.000187)
% Change	-1.73%	-3.09%	-0.98%	-4.72%	-2.37%	-2.46%
P-value	0.8177		0.5241		0.9891	
Panel C: Cart Value						
Treat	-0.819	-0.723	-0.242	-1.733	-1.546	0.0417
	(1.258)	(1.608)	(1.215)	(1.714)	(1.567)	(1.159)
% Change	-2.48%	-2.07%	-0.74%	-4.87%	-3.69%	0.16%
P-value	0.9452		0.5023		0.4771	
Observations (Panel A&B)	714,872	529,144	714,642	529,374	714,642	529,374
Observations (Panel C)	2,906	1,905	3,126	1,685	2,347	2,464

[1] Refer to Table F1 for detailed notes.