From Aversion to Adoption: The Role of Promotion Design in Mitigating Algorithm Aversion

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Abstract. Despite rapid advances in artificial intelligence (AI), adoption is often hindered by algorithm aversion, a psychological reluctance to trust algorithmic systems. Overcoming this barrier is critical for realizing the potential of AI innovations. While prior research has primarily focused on system–based solutions, we examine a widely adopted economic incentive, price promotions, whose effectiveness in reducing algorithm aversion has yet to be examined. In collaboration with a leading global e-commerce platform, we conducted a field experiment involving 26,276 existing platform users who had never previously used autonomous delivery vehicles. Participants are randomly assigned to a control group, a single-stage promotion (one-time offer) group, or a multi-stage promotion (a series of discounts) group. Our results show that while promotions trigger initial trials for autonomous delivery, they also risk cannibalizing full-price orders during the promotional period. Nevertheless, customers who received coupons exhibit a significant increase in full-price adoption of autonomous delivery relative to the control group after the promotions end. Furthermore, we find the single-stage strategy spurs a trial but cannibalizes full-price sales and has no lasting impact. By contrast, the multi-stage strategy drives adoption more than five times greater than the single-stage, generates positive spillovers to full-price orders even during the promotional period, and fosters sustained long-term use. Its effectiveness follows an inverted U-shaped, peaking at an average coupon interval of 11 days and a discount depth of 51%. Subsequent heterogeneous analyses uncover the patterns behind these divergent outcomes. Customer habituation to self-pickup tends to undermine the limited benefits of the single-stage strategy, while it amplifies the effectiveness of the multi-stage strategy. Moreover, the effectiveness of both strategies is also contingent on service reliability, as delivery failures ultimately undermine their efficacy. Overall, our study provides a scalable blueprint for designing promotions to build trust, reduce algorithm aversion, and sustain the adoption of AI technologies.

Key words: autonomous vehicles, AI technology, algorithm aversion, price promotions, field experiment.

1. Introduction

Artificial intelligence (AI) and algorithmic decision-making are poised to fundamentally reshape modern society through large-scale automation and optimization (Wang et al. 2023a, Ni et al. 2025). A particularly transformative frontier lies in autonomous mobility, where autonomous delivery vehicles promise a scalable and efficient solution for last-mile logistics. Equipped with sophisticated AI-powered sensors, machine learning models, and complex navigation systems, these vehicles can streamline the delivery process, yielding benefits such as lower operational costs, shorter delivery times, and greater convenience. However, the success of such technologies depends not only on their technical capabilities but also on public acceptance and adoption. A significant barrier to this adoption is algorithm aversion, a well-documented psychological tendency for humans to distrust and reject advice or services from an algorithm, even when it outperforms human judgment (Dietvorst et al. 2015, Guo and Li 2025). For instance, KPMG's 2023 report on global perceptions of AI found that 61% of respondents are wary of trusting AI systems, with this skepticism being particularly pronounced in economically developed countries such as the United States (KPMG 2023). In practice, algorithm aversion could manifest as user inertia, heightened risk perception toward novel systems, and a preference for familiar, human-based alternatives, especially during initial adoption. Therefore, overcoming this psychological resistance is critical to unlocking the full societal and economic potential of AI-driven innovations.

To date, research on mitigating algorithm aversion has primarily focused on AI system-based interventions (Burton et al. 2020, Reich et al. 2023, Hao and Xu 2025). Scholars have explored solutions such as allowing users to modify the algorithm outputs or reframing algorithmic advice to leverage psychological biases like loss aversion (Dietvorst et al. 2018, Cowgill and Tucker 2020, Bockstedt and Buckman 2025). In contrast, this study shifts the focus to a well-established economic incentive, price promotions, an approach widely examined in other domains but not yet explored for its effectiveness in reducing algorithm aversion. Promotions like coupons are traditionally used as an economic lens for their ability to lower the financial barrier to purchase (Klenow and Malin 2010, Zhang et al. 2020, Fang et al. 2021). However, in the context of AI adoption, financial costs may only be part of the hurdle; customer hesitation is often driven more by psychological barriers such as algorithm aversion. For skeptical customers, the cost of trying autonomous delivery vehicles is not merely financial; it includes a bundle of psychological costs rooted in this aversion, such as the anxiety of engaging with an unfamiliar, non-human agent, inherent distrust of its algorithmic judgment, and the cognitive effort required to navigate this novel technology. Therefore, if promotions are to be effective in this context, they likely need to do more than reduce a one-time financial cost. By lowering the perceived risk of trial, they may provide hesitant customers with a low-stakes opportunity to experience the technology, thereby beginning to ease psychological barriers. This raises a critical question: Can price promotions serve as psychological nudges that not only incentivize an essential first-hand experience but also encourage a durable habit of technology adoption?

Furthermore, when confronting a deep-seated bias like algorithm aversion, the design of a promotion becomes crucial, as its structure may shape customer perceptions and behavioral responses (Lee and Charles 2021, Ghose et al. 2024). For instance, a company might employ the simple first-time-free coupon (a single-stage strategy) or implement a more sustained campaign where customers receive a series of coupons over time (a multi-stage strategy). The two approaches may signal different psychological propositions to customers, raising the question of whether a single-stage strategy is sufficient to overcome such a deeply rooted barrier. In contrast, a multi-stage strategy may better encourage initial trials, but its repeated discounts risk anchoring customers to lower reference prices and discouraging full-price adoption. Understanding how these promotional designs may affect algorithm aversion differently is, therefore, a critical question.

To systematically investigate these dynamics, we adopt a framework that decomposes the impact of price promotions along three key dimensions: their spillover beyond the initial incentivized trial, the temporal horizon of their effects, and the structure of the promotional strategy. This approach allows us to move beyond asking whether promotions work toward a more nuanced understanding of how, when, and why they mitigate algorithm aversion. In what follows, we discuss each of these three dimensions in turn.

First, a promotion could serve as a direct trigger for technology adoption, as the reduced financial cost may provide the necessary justification for skeptical customers to try autonomous delivery for the first time. Beyond this immediate, incentivized effect, a key uncertainty lies in the promotion's spillover effect during the promotional period. One perspective is that promotions cannibalize revenue by attracting opportunistic users who engage only with a discount, rendering the effect purely transactional (Reimers and Xie 2019). Alternatively, the initial trial may encourage a deeper re-evaluation of the technology, persuading hesitant customers to use it again at full price even before the promotion ends.

Another critical consideration is sustainable adoption, or the long-term effect after the promotional period ends. One possibility is that the behavioral change is transitory, closely tied to the discount, such that baseline aversion resurfaces once the incentive is withdrawn (Zhang et al. 2020). Conversely, firsthand experience gained during the promotion might provide tangible evidence that counters prior uncertainties, leading to a preference shift and habit formation. This would foster sustained use after the promotion, signaling a lasting reduction in algorithm aversion. These contrasting possibilities prompt us to investigate how price promotions influence adoption across time, focusing on their short-term effects (trigger and spillover) and their long-term impact on first-time users of autonomous delivery.

Next, we consider the distinct impacts of the two promotional strategies. A single-stage strategy, while simple to implement and relatively low cost, may be inadequate to overcome substantial psychological barriers. By offering a one-time incentive limited to the initial transaction, this strategy might fail to provide enough motivation for hesitant customers to commit to a first trial. Furthermore, even if a trial occurs, it is unclear whether a single incentivized experience can meaningfully reduce underlying aversion. Hence, the ability of this strategy to generate broader benefits, such as a positive short-term spillover effect and long-term behavioral change, remains questionable, as customer engagement may cease once the promotion is redeemed.

In contrast, a multi-stage strategy offers repeated nudges that increase the likelihood of a technology trial (Thaler and Sunstein 2009), but it also might introduce a trade-off. On one hand, a continuous stream of discounts may substantially lower customers' reference price and inadvertently train them to wait for promotions. This behavior could inhibit full-price adoption (DelVecchio et al. 2007), generating negative short-term spillover effects and weakening long-term retention. On the other hand, each incentivized use of autonomous delivery serves as a familiarization opportunity. Drawing on habit formation theory (Verplanken and Aarts 1999), such repeated, lower-risk exposures could build trust and provide the tangible experience needed to erode algorithm aversion (Castelo et al. 2019), fostering a positive spillover effect and habitual, non-incentivized adoption. The tension between training customers to expect discounts and helping them overcome their aversion presents an empirical puzzle. Therefore, it is crucial to explore how different promotional designs, specifically, the single-stage and multi-stage strategies, affect short-term (trigger and spillover) and long-term adoption patterns of autonomous delivery vehicles.

Building on this framework, we examine how two pivotal factors, customers' habituation to self-pickup, which reflects their behavioral inertia of adopting autonomous vehicles, and their exposure to delivery failures, which shapes trust in the technology, moderate the effectiveness of single-stage and multi-stage promotional strategies. By incorporating these behavioral dimensions, our analysis further identifies patterns that either foster or hinder the reduction of algorithm aversion.

First, we examine the moderating effects of habituation on the self-pickup model. For customers in the single-stage group, strong habituation may weaken the strategy's limited impact, as a simple incentive is unlikely to overcome such behavioral inertia. In contrast, the multi-stage strategy's efficacy is likely enhanced for these habituated customers, as the structured sequence of incentivized interactions might serve as an effective behavioral intervention. We next consider the experience of delivery failures. The single-stage strategy might be vulnerable to such negative events. For customers in this strategy, a delivery failure not only confirms initial bias but also reinforces distrust, discouraging future engagement with this technology (Anderson et al. 2009). By contrast, the multi-stage strategy may offer inherent resilience. The sequence of promotions might function as an effective recovery tool, acting as both a tangible amends to give the technology another try.

To address these empirical puzzles, we partnered with a leading global e-commerce platform to conduct a randomized field experiment within its last-mile network on university campuses. On these campuses, students typically self-pick up packages, creating substantial last-mile inconvenience. To alleviate this issue, the platform introduced autonomous delivery vehicles in 2019 as a more convenient alternative. Our experiment, which ran from March 2 to April 1, 2023, targets first-time customers of autonomous delivery and employs a two-stage randomization procedure to assign promotional coupons. In the first stage, these customers are randomly assigned to either a control group, which receives no promotion, or a treatment group. In the second stage, participants in the treatment group are further randomized into one of two promotional strategies. Customers in the single-stage strategy receive the first-time-free coupon, valid only for their initial use of autonomous delivery. Meanwhile, those in the multi-stage strategy receive the same initial coupon and are eligible for subsequent coupons with varying discount levels (i.e., 20%, 40%, 60%, 80% off).

Our dataset tracks the daily activities of 26,276 first-time autonomous delivery customers from February 1 to May 1, 2023, including package arrivals, pick-up approaches, autonomous delivery orders, as well as coupon issuance and redemption. All customers in the sample had received *at least one* package in the preceding year but had *never* used autonomous delivery. To address our research questions, we divide the observation window into three distinct phases. The pre-treatment period (February 1 to March 1) allows us to verify the integrity of our random assignment. This is followed by the treatment period (March 2 to April 1), during which we measure the promotion's short-term trigger and spillover effects. Finally, the post-treatment period (April 2 to May 1) enables us to assess the long-term impact of the promotions on customer habit formation with autonomous delivery vehicles after the promotion ends. Further details on the study's context and data are available in Section 3.

Our paper contributes to the information systems (IS) literature on AI technology application and adoption by offering the following insights. First, our results show that during the promotional period, while promotions can trigger initial trials of autonomous delivery, they also cannibalize full-price orders, creating a negative spillover effect. This short-term finding might suggest that promotions merely substitute full-price purchases with discounted ones and fail to cultivate sustained engagement with the technology. Yet, the long-term analysis reveals a different story. We find that customers who are offered promotions exhibit a significant increase in full-price adoption of autonomous delivery after the incentives have expired, indicating a durable behavioral shift rather than a purely transactional response.

Second, the tension between short-term costs and long-term gains motivates our careful investigation into promotional design, which shows that single-stage and multi-stage strategies yield distinct outcomes. The single-stage strategy proves to be a limited incentive. While triggering an initial trial, it simultaneously cannibalizes full-price orders and, critically, has no lasting impact on customer adoption of autonomous delivery. In contrast, the multi-stage strategy emerges as an effective tool for durable behavioral change. It not only drives significantly more trials but also generates a positive spillover effect, encouraging full-price orders during the promotional period. More importantly, this sustained engagement fosters a durable, long-term habit of autonomous delivery adoption, proving that repeated, low-risk interactions can dismantle psychological barriers. These contrasting outcomes highlight that mitigating algorithm aversion is not merely about whether to offer promotions, but how they are designed. We next analyze two key features of the multi-stage strategy related to its effectiveness: promotional frequency and intensity. Specifically, adoption outcomes of this approach exhibit an inverted U-shaped relationship with both factors, peaking at a time interval of approximately 11 days between coupon assignment and an average discount depth of about 51%.

Finally, we examine how these divergent outcomes are moderated by two key factors: habituation to the self-pickup model and delivery failures. First, customer habituation to self-pickup is a key factor that determines the effectiveness of the two promotional strategies. For the single-stage strategy, its limited benefits are significantly diminished for habituated customers, resulting in a weaker short-term trial effect and more pronounced revenue cannibalization. Conversely, the multi-stage strategy is particularly effective for this habituated segment, as its structured approach fosters stronger short-term engagement and a more rapid and durable transition to full-price adoption of autonomous delivery. Second, we find that the single-stage offer is particularly fragile in the face of delivery failures. Such a negative experience significantly weakens this strategy's ability to trigger trials and deepens the negative spillover effect. In contrast, delivery failures do not significantly weaken the multi-stage strategy's immediate trigger effect during the promotion, indicating customers may continue to redeem coupons despite a failure. This resilience, however, does not extend to deeper behavioral change, as we observe a significant and negative interaction effect of delivery failures on both the positive spillover and the long-term adoption. These findings demonstrate that while promotional incentives have the potential to foster trust, they cannot rebuild it once broken.

The rest of this paper is structured as follows. We begin by reviewing the relevant literature (Section 2) and describing the field setting and data (Section 3). We then present our main empirical analysis, first by estimating the effects of price promotions on autonomous delivery adoption in Section 4 and then by investigating the distinct effectiveness of two promotional strategies in Section 5. Subsequently, we provide a more granular, heterogeneous analysis (Section 6) and conduct a series of robustness checks to validate our main findings (Section 7). Finally, Section 8 offers concluding remarks.

2. Literature Review

This study is closely related to three streams of literature: (i) algorithm adoption and aversion, (ii) price promotions on online platforms, and (iii) AI technology applications in information systems.

2.1. Algorithm Adoption and Aversion

Our study contributes to the burgeoning literature on algorithm aversion, the persistent human tendency to distrust and underutilize algorithmic systems (Burton et al. 2020, Jussupow et al. 2020, Xu et al. 2024, Wang et al. 2025a). Seminal research shows this aversion is often triggered by users' low tolerance for algorithm errors, leading to a more rapid loss of confidence compared to human counterparts (Dietvorst et al. 2015, Dietvorst and Bharti 2020). Subsequent work has identified a rich set of drivers, including psychological factors like a perceived lack of control over opaque black-box processes (Cowgill and Tucker 2020, Cadario et al. 2021) and task subjectivity (Castelo et al. 2019), as well as contextual factors such as a mismatch with human expertise (Luo et al. 2019, Allen and Choudhury 2022), social influence and information disclosure (Dargnies et al. 2024, Sun et al. 2024, Liu et al. 2025), and algorithm implementation costs (Kawaguchi 2021). In response, scholars have explored interventions to mitigate this aversion, focusing primarily on AI system–based solutions (often) tested in controlled laboratory settings. These include granting users the ability to modify algorithmic outputs (Dietvorst et al. 2018), reframing algorithmic decisions to leverage psychological biases like loss aversion (Bockstedt and Buckman 2025) or to incorporate human knowledge

(Greiner et al. 2025), and highlighting an algorithm's capacity to learn from mistakes (Reich et al. 2023). Building on prior studies, our work contributes to this literature along two key dimensions. First, we shift attention to a different intervention: price promotions. Although widely used in other domains, their potential to mitigate algorithm aversion has not been systematically examined. To our knowledge, we are the first to systematically examine how price promotions can serve as a psychological nudge to overcome algorithm aversion. Second, we move beyond the controlled laboratory settings and conduct a large-scale randomized field experiment to causally assess the short- and long-term effects of price promotions in alleviating such psychological hurdles, echoing the urgent call for offering more robust and real-world evidence on algorithm aversion (Liu et al. 2025).

2.2. Price Promotions on Online Platforms

Price promotions, temporary incentives designed to lower the financial barrier to purchase (Anderson and Fox 2019), have long been a cornerstone of marketing strategy. Traditionally, research rooted in brick-and-mortar settings focuses on promotions' economic and competitive effects, such as the impact on the demand for the promoted brand (Pauwels et al. 2002, Anderson and Simester 2004), the corresponding product category (Nijs et al. 2001, Pauwels et al. 2002), and even adjacent categories (Erdem and Sun 2002, Arora and Henderson 2007). The advent of online platforms, however, has reshaped this landscape. Unlike the brand- or product-level discounts common in physical stores, online platforms enable merchants to implement personalized and dynamic promotional strategies, raising new questions about customer responses in a digital environment (Mejia et al. 2020, Wang and Lu 2024, Aseri et al. 2024). Consequently, recent research has begun to unravel these complexities, revealing several critical trade-offs and nuances. For instance, while promotions boost short-term engagement, they also foster undesirable long-term strategic behavior such as heightened price sensitivity (Zhang et al. 2020). Other work highlights the tension between expanding the user base and cannibalizing revenue from existing customers when employing promotions (Reimers and Xie 2019). Moreover, the way a promotion is framed, such as discounting a product's base price versus reducing a surcharge, affects customer perceptions of quality (Wu et al. 2021), and can even create unintended opportunity costs by crowding out other purchases (Fong et al. 2019). Despite these advances, little is known about the temporal impact of promotions on overcoming significant psychological barriers to technology adoption. Our study addresses this gap by examining how promotions affect the adoption of autonomous delivery among existing customers who have been reluctant to try the technology across different time horizons and decision points. We further extend this stream of research by comparing two widely used but understudied promotional strategies, single-stage and multi-stage, and by identifying how they differ in their effectiveness at mitigating algorithm aversion. To provide a more granular understanding, we also explore how habituation to the self-pickup model and experience with delivery failure influence the effects of these two strategies. Together, these insights offer a comprehensive framework for deploying online promotions to reduce psychological resistance and facilitate behavioral change in the context of AI-driven innovations.

2.3. AI Technology Applications in Information Systems

This study is also closely connected to the IS literature on the application of AI technologies. As AI rapidly advances, IS scholars have increasingly examined the impact of diverse AI applications across business contexts (Berente et al. 2021, Han et al. 2023, Wang et al. 2024a, Zheng et al. 2025). For example, in e-commerce, voice and livestreaming AI assistants have enhanced customer spending and sales (Hao and Xu 2025, Sun et al. 2025, Wang et al. 2025b), while machine translation boosts international trade (Brynjolfsson et al. 2019). Studies of human–AI interaction show that anthropomorphic chatbots increase transaction conversion in the retail setting (Schanke et al. 2021) and build trust in freight dispatching (Xu et al. 2024), AI competitors reshape labor strategies (Lysyakov and Viswanathan 2023), voice-based AI reduces call center complaints (Wang et al. 2023b), and AI models improve financial inclusion for underserved populations (Li et al. 2024). More recently, scholars have turned their attention to generative AI, emphasizing its role in influencing creativity (Zhou and Lee 2024, Liang et al. 2025a,b), market efficiency (Rusak et al. 2025, Wiles and Horton 2025), and knowledge sharing behavior (Su et al. 2023). Beyond organizations, AI technologies have demonstrated a broader societal impact, from education apps mitigating learning loss during the pandemic (Ko et al. 2023) to machine learning systems shaping the productivity of knowledge workers, often contingent on user trust and experience (Van den Broek et al. 2021, Wang et al. 2024b). Taken together, this body of work primarily examines the impact of AI technologies after their implementation. Our work contributes to the existing literature in two major ways. First, rather than focusing on the impact of AI implementation, we address the challenge of AI adoption, an essential yet underexplored step in realizing AI's potential. Specifically, we examine how different price promotion strategies influence adoption by mitigating algorithm aversion. Second, we situate this challenge within a novel and increasingly important business context of autonomous vehicles for last-mile logistics. By examining how promotional design alleviates algorithm aversion, our study provides new insights into how companies can bridge the gap between deploying an AI technology and achieving its widespread, habitual use.

3. Context and Data

3.1. Field Setting and Experimental Design

In collaboration with a leading global e-commerce platform, we conduct a field experiment on its autonomous delivery vehicles. Our study is set within the platform's extensive last-mile delivery network on university campuses, where students, most of whom live in on-campus dormitories, collect packages from centralized pickup hubs. Before the launch of those autonomous delivery vehicles, the platform use a self-pickup model, which requires students to walk to the station and wait for the staff to retrieve their packages, creating a significant last-mile inconvenience.

To address this challenge, the platform introduced an on-demand delivery service in 2019 using autonomous delivery vehicles. These autonomous vehicles are equipped with advanced AI-powered sensors for navigation, feature secure, code-accessible lockers for package safety, and integrate with the platform's app for real-time tracking and delivery notifications. By providing a convenient alternative to self-pickup, the autonomous delivery technology offers a promising solution to the last-mile challenge. The relatively controlled traffic conditions on campus provide an ideal setting for autonomous delivery deployment. An illustration of the platform's autonomous vehicles is provided in Figure A.1 in the Appendix.

Since the launch of its autonomous delivery service, the platform has observed non-negligible adoption barriers, with many customers exhibiting psychological resistance to trying this novel AI-driven technology. To address these hurdles, which are characteristic of algorithm aversion, we collaborated with this platform to design and implement a promotional program that ran from March 2 to April 1, 2023. The program targeted customers who had received *at least one* package in the preceding year but had *never* used autonomous delivery. This group represents an ideal population with ingrained psychological barriers that inhibit the first-time adoption of AI-driven technologies. Using a two-stage randomization procedure based on anonymized user IDs, these first-time users are randomly assigned to one of three experimental conditions.

In the first stage, customers are randomly assigned to either the control group, which receives no promotions, or the treatment group that is offered promotional coupons. This stage allows us to establish a baseline for autonomous delivery adoption and measure the causal effect of receiving the promotion. In the second stage, customers in the treatment group are further randomized to one of two subgroups. The first subgroup (the single-stage strategy) receives the first-time-free coupon applicable only to their initial use of autonomous delivery. The second subgroup (the multi-stage strategy) not only receives the first-time-free coupon, but also is eligible for subsequent coupons with randomly varying discount levels (i.e., 20%, 40%, 60%, 80% off) throughout the promotional period.

All coupons are issued daily at 0:00 and expire at 23:59 on the same day, but they can be applied to packages scheduled for delivery up to the following day. We provide an example of redeeming a 40% off coupon for autonomous delivery at the platform's app in Figure A.2 in the Appendix. Each customer's group assignment remains fixed throughout the study. The two-stage randomization design enables us to estimate the causal impact of receiving price promotions (by comparing the treatment and control groups) on mitigating algorithm aversion and to measure the distinct effects of the two promotional strategies.

3.2. Data and Randomization Check

This field experiment involves 26,276 existing platform users who had never used autonomous delivery vehicles from this platform's twelve stations. Because this study focuses on algorithm aversion, a user's reluctance to adopt autonomous vehicles in our context, we specifically exclude individuals with prior experience using these vehicles. We also exclude customers who are entirely new to the platform, as it is challenging to clearly attribute their non-adoption to aversion. Therefore, our experiment only consists of existing platform users, those who had collected at least one package previously, but are first-time users of autonomous delivery before our experiment. To ensure our study effectively targets users exhibiting aversion, we further test alternative thresholds of 5, 10, and 15 prior package collections in Section 7.1. The results remain highly consistent, confirming the validity of our approach. Our dataset comprises their daily activity from February 1 to May 1, 2023, including package information, pick-up approaches, autonomous delivery orders, as well as coupon issuance and redemption. Notably, no other major promotions targeted these customers during our observation window. Our analysis spans three distinct periods, as illustrated in the timeline in Figure 1:

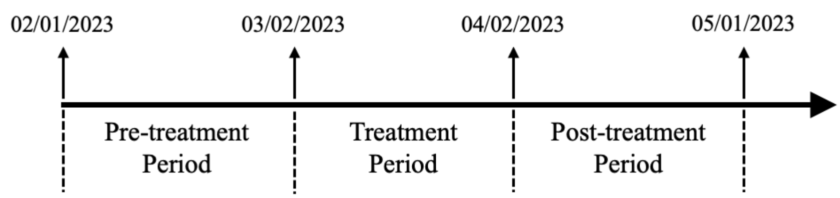

Figure 1 Study Timeline

The first period is the *pre-treatment period* from February 1 to March 1, 2023. Data from this month are used to confirm the validity of our random assignment by comparing baseline characteristics across the experimental groups. The second period is the *treatment period* from March 2 to April 1, 2023. During this intervention phase, customers in the treatment group received promotions as described in Section 3.1, while the control group received none. We use data from this period to estimate the short-term effects of the promotions, specifically, immediate autonomous delivery adoption (the trigger effect) and subsequent full-price usage (the spillover effect). The final period is the *post-treatment period* from April 2 to May 1, 2023, during which no promotions were offered to any groups. Data from this month allows us to assess the long-term (i.e., post-promotion) impact of promotions on sustained adoption and habit formation.

To validate our causal estimates, we perform a randomization check by comparing key pre-treatment characteristics at both the customer and station levels. At the customer level, we examine prior autonomous delivery adoption history and mobile device type (iOS vs. other), with the latter serving as a proxy for unobserved traits like tech-savviness and price sensitivity (Bailey et al. 2022). At the station level, we check for balance on three critical operational factors: (i) the number of available autonomous vehicles, capturing supply-side capacity; (ii) the average price of autonomous delivery, reflecting a key demand-side factor; and (iii) the prior year's package volume, which proxies for a station's overall scale and activity. Because customers are randomized across twelve stations, verifying balance on these station-level factors is crucial to account for potential site-specific effects.

As shown in Table 1, the treatment and control groups are well-balanced across these important observable metrics. By design, Column (1) shows that all customers in our sample placed zero autonomous-delivery orders before our experiment (i.e., before March 1, 2023), highlighting pre-existing barriers to adoption. Moreover, Columns (2) through (5) indicate no statistically significant differences in user device preference or station-level characteristics. Taken together, these results provide a solid foundation for attributing subsequent differences in adoption behavior to our promotional interventions. In Section 5, we conduct additional randomization checks to confirm the balance between our two treatment subgroups and the control group.

Table 1 Randomization Check for Treatment and Control Groups

	Autonomous Delivery Orders (Before March 1, 2023)	Proportion of iPhone Users	Station Autonomous Vehicle Count	Average Autonomous Delivery Price (RMB)	Prior-Year Station Package Volume
Groups	(1)	(2)	(3)	(4)	(5)
Treatment Group	0.000	0.261	2.943	2.416	1,045,666
Control Group	0.000	0.263	2.953	2.413	1,043,046
Difference	0.000	−0.002	−0.010	0.003	2,620
t-Test p-value	—	0.8121	0.4214	0.6659	0.6070

Note. This table reports the means of key pre-treatment variables for the treatment and control groups. Because the sample comprises first-time autonomous-delivery customers, prior orders are mechanically zero, yielding the result reported in Column (1). The unit of observation for the t-tests is the customer (*N*= 26,276).

3.3. Model Specification

In this section, we introduce the econometric model used to estimate the impact of price promotions on autonomous delivery adoption. Leveraging the randomized nature of our experiment (Kumar and Mehra 2024), we employ the following ordinary least squares (OLS) regression specification for customer i on date t:

$$Outcome_{i,t} = \beta_0 + \beta_1 \times Treatment_i + StationFE + DateFE + \epsilon_{i,t}, \tag{1}$$

where $Outcome_{i,t}$ is the behavioral outcome of interest, which will be explained later. In our main analysis, we apply a logarithmic transformation to this variable to mitigate right-skewness in the data and stabilize the variance. $Treatment_i$ is an indicator variable equal to 1 if customer i was assigned to the treatment group (receiving coupons) and 0 if assigned to the control group. We incorporate station fixed effects, $StationFE$, to control for any time-invariant factors specific to each station, such as its location, size, and operational hours. We also include date fixed effects, $DateFE$, to absorb time-specific shocks common to all customers, such as day-of-the-week patterns, holidays, and weather conditions. $\epsilon_{i,t}$ represents the idiosyncratic error term. In this specification, our coefficient of interest is β_1, which captures the causal effect of receiving the promotion on the outcome variable.

To address our research questions, we adapt this main model (Equation 1) in two ways. First, we vary the definition of the outcome variable and the observation period to distinguish between short- and long-term effects. To estimate the immediate trigger effect on adoption during the promotional period (March 2 – April 1), we define $Outcome_{i,t}$ as the total number of autonomous delivery orders placed by customer i on date t. To assess the potential spillover effect where promotions might cannibalize or stimulate regular sales within the same period, we conduct a parallel analysis defining $Outcome_{i,t}$ as the number of full-price autonomous delivery orders. Finally, to evaluate long-term (i.e., post-promotion) effects on habit formation, we shift our focus to the post-treatment period (April 2 – May 1) and re-estimate the model using both the total number of autonomous delivery orders and the number of full-price autonomous delivery orders as outcome variables.

Second, to differentiate the impact of each promotional strategy, we estimate Equation 1 on two distinct subsamples. To measure the effectiveness of the single-stage strategy, we use a subsample containing only the single-stage promotion group and the control group. In this regression, $Treatment_i$ equals 1 only for customer i assigned to the single-stage promotion. The resulting β_1 coefficient quantifies the causal impact of this strategy relative to no promotion. We then conduct a parallel analysis for the multi-stage strategy using a subsample of the multi-stage promotion group and the control group. Here, $Treatment_i$ equals 1 only for treated customers in the multi-stage group, and the corresponding β_1 measures this strategy's causal effect on autonomous delivery adoption.

To further ensure the reliability of our findings, we conduct several robustness checks. First, while our main results are reported with robust standard errors, they remain highly consistent when clustering standard errors at the customer level (see Section 7.3). Second, to confirm our results are not an artifact of our outcome variable's definition, we re-estimate Equation 1 with alternative dependent variables, including the raw autonomous delivery order count (without logarithmic transformation), a binary indicator for placing an autonomous delivery order, and the percentage of autonomous delivery orders among a customer's total packages. These alternative specifications yield highly consistent results, reinforcing the validity of our main findings (see Section 7.4).

4. Effects of Price Promotions on Autonomous Delivery Adoption

In this section, we estimate the impact of price promotions on customers' adoption of autonomous delivery. We first examine the short-term effects during the promotional period (March 2 - April 1, 2023) and subsequently investigate the long-term effects after the promotions ended (April 2 - May 1, 2023) to assess whether the induced behavior is sustainable.

4.1. Short-Term Trigger and Spillover Effects of Price Promotions

To understand the immediate impact of the price promotion, we analyze customer behavior in adopting autonomous delivery during the treatment period. Price promotions can have two distinct effects in the short term: the trigger effect, a potential direct increase in orders driven by the coupon, and the spillover effect, a change in full-price orders from the same customers during the promotional period. A positive spillover would suggest the promotion encourages a broader re-evaluation of autonomous delivery, while a negative spillover would indicate revenue cannibalization.

Using Equation (1), we obtain the results in Table 2, which reveal a nuanced short-term impact. First, we find evidence of the trigger effect. The coefficient for $Treatment$ in Column (2) is positive and statistically significant (β = 0.0160, $p < 0.001$), indicating that the coupon offer increases customer adoption of autonomous delivery. To quantify the economic significance of this treatment effect, we examine the model using the raw count of autonomous delivery orders as the outcome (see Section 7.4 for further details). This analysis shows that the increase driven by the promotion corresponds to 90.5% of the average daily autonomous delivery orders among treated customers during the promotional period. This figure is calculated by dividing the treatment effect from the raw count model in Column (1) of Table A.10 in the Appendix (0.0278) by the average daily autonomous delivery orders for treated customers during the promotional period (0.0307). These results suggest that price promotions are effective in encouraging hesitant first-time users to trial autonomous delivery.

However, this positive trigger effect comes with a trade-off. When focusing exclusively on full-price autonomous delivery orders in Column (4), the coefficient for $Treatment$ turns negative and statistically significant (β = -0.0006, $p < 0.001$). This negative spillover suggests a potential degree of cannibalization. Customers in the treatment group who received coupons may be less likely to place full-price orders compared to those in the control group. This finding could be driven by strategically substituting a planned full-price purchase with a discounted one or delaying purchases until a coupon becomes available. To corroborate our findings on short-term cannibalization effects, we perform two robustness checks in Section 7.6. First, we exclude customers who redeemed the first-time-free coupon but had no subsequent packages. This ensures the observed negative spillover effect is not driven by a segment of customers who had no opportunity to place full-price autonomous delivery orders after coupon redemption. Second, to better capture customers' propensity to place full-price autonomous delivery orders on days without promotions, we exclude customer-day observations when a coupon is used and re-run the analysis employing the proportion of full-price autonomous delivery orders among a customer's total packages as the dependent variable. Both analyses yield highly consistent results, reinforcing our conclusions.

Table 2 Short-Term Effects of Price Promotions on Autonomous Delivery Adoption

	log(*Num. of Orders*)		log(*Num. of Full Price Orders*)	
Variables	(1)	(2)	(3)	(4)
$Treatment$	0.0160***	0.0160***	-0.0006^{***}	-0.0006^{***}
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Date Fixed Effects	No	Yes	No	Yes
Station Fixed Effects	Yes	Yes	Yes	Yes
Observations	814,556	814,556	814,556	814,556
R-squared	0.0097	0.0103	0.0006	0.0007

Note. Robust standard errors are given in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Notably, it is possible that some customers in the treatment group did not redeem their coupons, so our estimates represent a conservative intention-to-treat (ITT) effect. To address this potential concern, in Section 7.2, we conduct a robustness check for all short-term analyses by employing a two-stage least squares (2SLS) approach to estimate the average treatment effects of redeeming promotions, and the results remain highly consistent under this specification.

4.2. Long-Term Effects of Price Promotions

We next examine the long-term effects of the promotion to determine whether it can mitigate algorithm aversion post-promotion. If the behavioral change is fleeting and tied only to the financial incentive, customers should revert to their baseline (pre-promotion) behavior once the incentive expires. However, if the incentivized trial provides tangible evidence that counters prior fears and uncertainties, it could lead to a sustained preference shift and the formation of a new habit.

To answer this crucial question, we analyze customer behavior after the promotional period (April 2 - May 1, 2023), when no promotions were available to either group. We apply the same regression model specified in Equation (1), where the $Treatment$ variable remains defined by the original random assignment. We again examine two outcome variables: the number of autonomous delivery orders and the number of full-price autonomous delivery orders. Because customers could schedule autonomous delivery orders up to the following day, some coupon-based orders placed during the promotional month might be fulfilled on April 2. To ensure our long-term analysis captures sustained, un-incentivized behavior, as a robustness check, we re-estimate the long-term effects excluding observations from April 2 to remove potential carryover effects from the promotion. As detailed in Section 7.5, the results remain highly consistent, which provides additional support to our findings.

Table 3 Long-Term Effects of Price Promotions on Autonomous Delivery Adoption

	log(*Num. of Orders*)		log(*Num. of Full Price Orders*)	
Variables	(1)	(2)	(3)	(4)
$Treatment$	0.0013***	0.0013***	0.0013***	0.0013***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Date Fixed Effects	No	Yes	No	Yes
Station Fixed Effects	Yes	Yes	Yes	Yes
Observations	788,280	788,280	788,280	788,280
R-squared	0.0010	0.0013	0.0010	0.0013

Note. Robust standard errors are given in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

The results in Table 3 provide evidence for a lasting behavioral change. In Column (2), the coefficient for $Treatment$ is positive and statistically significant (β = 0.0013, $p <$ 0.001), indicating that customers initially offered coupons place more autonomous delivery orders than the control group after the promotion ends. To assess the economic significance, we again use the raw-count specification in Section 7.4 and find that the estimated increase represents 34.9% of the treated customers' average daily autonomous delivery orders in the post-promotion period. This is calculated by dividing the treatment effect from the raw count model in Column (2) of Table A.10 in the Appendix (0.0022) by the average daily autonomous delivery orders for treated customers during the post-promotion period (0.0063). Crucially, this is not an artifact of delayed coupon fulfillment. The result in Column (4), which only focuses on full-price orders, reveals a nearly identical positive and significant effect (β = 0.0013, $p < 0.001$). This confirms that the lift in autonomous delivery adoption is driven by new, full-price purchases, not by a backlog of discounted orders. This sustained increase in technology adoption after the financial incentive was removed suggests that the promotion's impact is more than transactional.

Taken together, the above short- and long-term findings also present a paradox: promotions can foster long-term adoption but simultaneously cannibalize full-price sales in the short term. This tension between building habits and eroding immediate revenue suggests a more complex mechanism is at play beyond the simple question of whether to offer promotions or not. Rather, it potentially lies in how their design, single-stage versus multi-stage, might differentially shape customer adoption. Therefore, in what follows, we examine how the two promotional strategies exert distinct effects on first-time customers' adoption of autonomous delivery.

5. Further Analyses on Two Promotional Strategies

Our findings thus far establish that price promotions can drive long-term adoption while incurring short-term cannibalization. This trade-off motivates a deeper investigation into the design of the promotional strategy, as it may shape how customers perceive and respond to incentives. We consider two common strategies: a single-stage incentive, such as only offering the first-time-free offer, or a multi-stage campaign that offers sustained discounts. Because these strategies may send different psychological signals, they could differentially influence customers' algorithm aversion. This leads to a critical question: Do single- and multi-stage promotions vary in their ability to mitigate algorithm aversion? To answer this, our experimental design partitions the treatment group into two subgroups: customers who received only the first-time-free coupon (the single-stage strategy) and those who received subsequent coupons (the multi-stage strategy).

5.1. Effects of the Single-Stage Promotional Strategy

Before analyzing the results, we first verify whether the single-strategy treatment subgroup and the control group are comparable in terms of key observable characteristics prior to the intervention. As detailed in Table A.1 in the Appendix, we find no statistically significant pre-treatment differences between the groups at either the customer or station level. The high p-values for device preference, number of available autonomous vehicles, autonomous delivery price, and number of packages handled by the station in the prior year confirm that the randomization is passed. This balance establishes a credible baseline for estimating the causal effect of the single-stage promotional strategy.

Based on its structure, we theorize that the single-stage strategy, while effective for encouraging an initial trial of autonomous delivery, is unlikely to foster sustained, long-term changes in customer preference. First, this promotional strategy could generate a positive trigger effect due to its ability to reduce customer hesitation, a key barrier to trying a novel technology (Mani and Chouk 2018). By making the first order free, the strategy eliminates the financial risk of experimentation and lowers the psychological barrier of engaging with the unknown. This provides hesitant customers with a compelling external justification to counteract their baseline aversion, making this incentive a potent tool for the narrow goal of inducing a first-time use.

However, this external justification may also be the strategy's main weakness. By framing the initial interaction in purely transactional terms, the promotion's appeal might rest on financial benefit rather than the intrinsic value of autonomous delivery. As a result, the offer may establish a problematic psychological anchor. With the first delivery being free, a customer's reference point for the technology's value is temporarily set to zero. A subsequent full-price order is therefore more likely to be perceived as a loss than a fair exchange. This perception could not only diminish the perceived value of the technology but also suppress demand at its regular price, leading to revenue cannibalization during the promotion (Reimers and Xie 2019).

Furthermore, this strategy is unlikely to drive long-term impacts on customer adoption. From a habit formation perspective, sustained behavioral change requires repeated action and positive reinforcement (Verplanken and Aarts 1999, Gardner and Rebar 2019), elements that the single-stage strategy lacks. More critically, customers exposed to this strategy are likely to attribute their trial solely to the external incentive (e.g., "I tried it because it was free") rather than an internal shift in preference (e.g., "I tried it and realized I like it"). Because the trial is attributed externally, the behavior is not internalized. As a result, the experience is cognitively framed as a one-off event driven by the promotion, instead of as a genuine discovery of the technology's intrinsic value. This framing leaves the customer's underlying algorithm aversion unaltered. Once the incentive is removed, customers are expected to revert to their prior behaviors. In short, this strategy may rent a trial, but it fails to cultivate a lasting habit.

To empirically test our claims, we apply Equation (1) to the treatment subgroup that receives only the first-time-free coupon and our original control group. Table 4 presents the estimation results, which reveal a pattern consistent with a purely transactional customer response. Column (1) demonstrates a significant increase in daily autonomous delivery orders for the treatment subgroup relative to the control group (β = 0.0071, $p < 0.001$), which confirms that the single-stage promotion strategy is effective at inducing the initial trial.

However, this action does not appear to foster a broader re-evaluation of autonomous delivery's value. Column (3) shows a significantly negative spillover effect ($\beta = -0.0011$, $p < 0.001$), indicating that treated customers are less likely to place full-price autonomous delivery orders during the promotional period. This finding suggests that instead of encouraging further exploration, the single-stage incentive narrowly focuses customer behavior on the single deal, cannibalizing the potential for full-price adoption in the short term. Following the similar approach in Section 4.1, we confirm this short-term cannibalization effect with two robustness checks. The results from these checks, presented in Section 7.6, closely align with our findings, offering additional validation.

Additionally, the results in Columns (2) and (4) for long-term impacts indicate that the single-stage strategy is not potent enough to reduce underlying aversion and build a new habit. After the promotion ends, we find no statistically significant difference in autonomous delivery ordering behavior between this treatment subgroup and the control group ($\beta = -0.0001$, $p > 0.1$), demonstrating that the first-time-free promotion is ineffective for fostering sustained adoption. The deep, one-time discount, while successful at generating an initial transaction, fails to provide the familiarity and tangible evidence needed to overcome a customer's baseline aversion. Once the financial incentive disappears, customers revert to their original behavior. These findings indicate that the single-stage strategy merely rents customers for their first order rather than creating a preference shift, highlighting the limitations of this approach.

Table 4 Effects of the Single-Stage Promotional Strategy

	log(*Num. of Orders*)		log(*Num. of Full Price Orders*)	
Variables	*(1) Short (3.2-4.1)*	*(2) Long (4.2-5.1)*	*(3) Short (3.2-4.1)*	*(4) Long (4.2-5.1)*
$Treatment$	0.0071***	−0.0001	−0.0011***	−0.0001
	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Date Fixed Effects	Yes	Yes	Yes	Yes
Station Fixed Effects	Yes	Yes	Yes	Yes
Observations	726,919	703,470	726,919	703,470
R-squared	0.0039	0.0009	0.0010	0.0009

Note. Robust standard errors are given in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

5.2. Effects of the Multi-Stage Promotional Strategy

The limited effectiveness of the single-stage strategy prompts a critical question: Can repeated exposure to promotions achieve better performance? Accordingly, this section focuses on customers in the multi-stage strategy. During our promotional period, these customers were randomly offered additional discounts of 20%, 40%, 60%, or 80% after the initial first-time-free coupon.

Similarly, we conduct a randomization check comparing this multi-stage subgroup against the control group. Table A.2 in the Appendix shows that the two groups are well-balanced across these measured pre-treatment covariates. This balance provides a valid foundation for attributing subsequent differences in autonomous delivery adoption behavior to the multi-stage promotional intervention, rather than to pre-existing disparities.

We theorize that the structure of a multi-stage promotional strategy encourages repeated customer interaction with autonomous delivery. Over time, these interactions help first-time customers overcome algorithm aversion and form a lasting habit of using the technology. First, the multi-stage strategy could produce a positive short-term trigger effect, potentially stronger than the single-stage offer. By presenting a sequence of coupons, it establishes a continuous incentive structure that encourages customers to engage with autonomous delivery multiple times. Drawing on prospect theory (Kahneman and Tversky 1979), each incentivized interaction serves as a low-risk opportunity, allowing customers to gain firsthand experience while reducing the perceived cognitive effort and operational complexity of using this technology. As these low-risk interactions accumulate, the process becomes more predictable and frictionless, shifting autonomous delivery from an unknown entity into a known tool. This growing familiarity might enhance the technology's perceived utility to a point where customers are willing to place full-price orders as their default choice (Vaidya et al. 2025). Hence, this strategy has the potential to generate positive spillover effects by cultivating familiarity, which contrasts with the single-stage strategy that makes customers reluctant to pay at full price.

Second, the long-term efficacy of this strategy hinges on converting familiarity into habitual use. In line with nudge theory (Thaler and Sunstein 2009), repeated positive exposure gradually reduces uncertainty and apprehension, replacing them with a stable, experience-based understanding and trust of the technology. This trust helps customers integrate autonomous delivery into daily routines (George et al. 2022), which could counteract algorithm aversion. By the end of the promotional period, customers not only acquire practical knowledge of the autonomous delivery technology but also recognize its intrinsic value beyond financial incentives. Their perception, now grounded in direct experience rather than abstract fear, becomes internalized. This shift in both attitude and behavior is likely to persist after the discounts cease, leading to sustained adoption of autonomous delivery.

Next, we examine the above claims by applying Equation (1) to the treatment subgroup that received the multi-stage coupons and the original control group. The estimation results in Table 5 show that the multi-stage strategy is effective at both triggering immediate trials and fostering the durable adoption of autonomous delivery. First, we observe a significant short-term trigger effect: the multi-stage promotion encourages customers to try autonomous delivery. As shown in Column (1), customers who received multiple coupons are more likely to place autonomous delivery orders (β = 0.0396, $p < 0.001$), an effect more than five times greater than that of the single-stage approach (multi-stage β = 0.0396 vs. single-stage β = 0.0071). Importantly, and unlike the single-stage strategy, the multi-stage approach can generate a positive spillover effect. Column (3) reveals a significant increase in autonomous delivery orders without using coupons (β = 0.0005, $p < 0.001$) during the promotional period. This is a crucial finding: instead of cannibalizing full-price sales, the repeated, incentivized interactions prompt familiarity and trust-building so effectively that customers begin placing full-price orders even while they may still receive discounts.

Second, our analyses further indicate that the benefits extend beyond the promotional period, cultivating a sustained behavioral shift. As shown in Column (2), customers in the multi-stage treatment subgroup continue to place more autonomous delivery orders after the promotional period ends (β = 0.0049, $p <$ 0.001). This lasting effect is not only statistically significant but also practically meaningful, especially when compared to the single-stage strategy. Column (4), which is restricted to full-price orders, corroborates this pattern. Together, these findings imply that a series of promotions allows customers to accumulate direct evidence of technology's utility and convenience. This cumulative experience builds trust and familiarity that outlasts the discounts, alleviating algorithm aversion and establishing a new habit.

In summary, these results show that the multi-stage strategy significantly outperforms the single-stage approach. In fact, we caution against relying on the single-stage promotion, as it not only fails to generate lasting adoption but also risks cannibalizing full-price sales. On the contrary, a multi-stage strategy leverages a promotional series not merely to trigger short-term trials, but to prompt familiarity and trust, thereby converting hesitant first-time customers into full-price adopters.

Table 5 Effects of the Multi-Stage Promotional Strategy

	log(*Num. of Orders*)		log(*Num. of Full Price Orders*)	
Variables	*(1) Short (3.2-4.1)*	*(2) Long (4.2-5.1)*	*(3) Short (3.2-4.1)*	*(4) Long (4.2-5.1)*
$Treatment$	0.0396***	0.0049***	0.0005***	0.0048***
	(0.0007)	(0.0003)	(0.0002)	(0.0003)
Date Fixed Effects	Yes	Yes	Yes	Yes
Station Fixed Effects	Yes	Yes	Yes	Yes
Observations	601,214	581,820	601,214	581,820
R-squared	0.0301	0.0025	0.0008	0.0025

Note. Robust standard errors are given in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

5.2.1. Calibrating Promotional Frequency and Intensity After establishing that the multi-stage promotional strategy can generate both short-term positive spillover effects and sustained autonomous delivery adoption, we next examine how two key features of this strategy, promotional frequency (the interval between coupon assignment) and intensity (the average discount depth), influence the transition to full-price use. We hypothesize that both factors follow a non-linear, inverted U-shaped relationship with full-price adoption. Regarding frequency, when coupons arrive too frequently, customers may feel overwhelmed or come to rely on discounts, which prevents them from developing a habit of full-price use. Yet, if the interval is too long, the momentum gained from familiarity and trust may dissipate, weakening engagement with autonomous delivery. Similarly, when it comes to discount intensity, a discount that is too small may fail to generate meaningful trial, while one that is too large risks undermining the perceived value of the technology and anchoring customers to an artificially low reference price. Both outcomes ultimately hinder the transition to sustained adoption at full price.

To test these hypotheses, we leverage our experimental design, in which both the timing (frequency) and discount level (intensity) of subsequent coupons are randomized for users in the multi-stage treatment group. This exogenous variation allows us to causally identify the relationship between these promotional design features and customer adoption outcomes. Specifically, we employ a quadratic regression model for the multi-stage treatment subgroup. To examine the effect of promotional frequency, we construct the variable, $Avg.\ Coupon\ Assign\ Interval$, which represents the average number of days between coupon assignments for treated customers in this subgroup. The results in Table 6 support our hypotheses. For both short- and long-term full-price adoption, we find a positive and significant coefficient for the linear term ($Avg.\ Coupon\ Assign\ Interval$) and a negative and significant coefficient for the quadratic term ($Avg.\ Coupon\ Assign\ Interval^2$) across four specifications, suggesting an inverted U-shaped relationship.

To translate these findings into practical insights, we focus on the models for full-price adoption (Columns 3 and 4). By calculating the vertex of this quadratic function in Column (3), we identify a turning point at approximately 11 days for the short-term spillover effect, with the long-term effect in Column (4) reaching its turning point at a slightly shorter interval. These results suggest that a cadence of roughly one to two weeks represents a critical balance point: frequent enough to keep autonomous delivery salient and encourage repeated trials, yet not so frequent that it induces promotional fatigue or erodes customers' initial positive momentum.

Table 6 Inverted U-Shaped Effect of Promotional Frequency Under Multi-Stage Strategy

	log(*Num. of Orders*)		log(*Num. of Full Price Orders*)	
Variables	*(1) Short (3.2-4.1)*	*(2) Long (4.2-5.1)*	*(3) Short (3.2-4.1)*	*(4) Long (4.2-5.1)*
$Avg.\ Coupon\ Assign\ Interval$	0.0085***	0.0011***	0.0001**	0.0011***
	(0.0002)	(0.0001)	(0.0000)	(0.0001)
$Avg.\ Coupon\ Assign\ Interval^2$	−0.0004***	−0.0001***	−0.0000*	−0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Date Fixed Effects	Yes	Yes	Yes	Yes
Station Fixed Effects	Yes	Yes	Yes	Yes
Observations	601,214	581,820	601,214	581,820
R-squared	0.0232	0.0022	0.0008	0.0022

Note. Robust standard errors are given in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Next, we investigate the role of promotional intensity by analyzing the average discount depth of all coupons received by customers in this treatment subgroup, denoted as $Avg.\ Coupon\ Depth$. The results, presented in Table 7, also reveal an inverted U-shaped relationship with full-price adoptions. The linear term ($Avg.\ Coupon\ Depth$) is positive and the quadratic term ($Avg.\ Coupon\ Depth^2$) is negative, both statistically significant across the four columns.

These findings shed light on the trade-off between offering a meaningful incentive and preserving the perceived value of autonomous delivery. The coefficients in Column (3) indicate a turning point in the curve at a discount depth of roughly 51%, with the long-term effect in Column (4) leveling off at a similar range.

Table 7 Inverted U-Shaped Effect of Promotional Intensity Under Multi-Stage Strategy

	log(*Num. of Orders*)		log(*Num. of Full Price Orders*)	
Variables	*(1) Short (3.2-4.1)*	*(2) Long (4.2-5.1)*	*(3) Short (3.2-4.1)*	*(4) Long (4.2-5.1)*
$Avg.\ Coupon\ Depth$	0.1571***	0.0198***	0.0028**	0.0191***
	(0.0058)	(0.0025)	(0.0011)	(0.0024)
$Avg.\ Coupon\ Depth^2$	−0.1363***	−0.0173***	−0.0028**	−0.0165***
	(0.0072)	(0.0030)	(0.0014)	(0.0030)
Date Fixed Effects	Yes	Yes	Yes	Yes
Station Fixed Effects	Yes	Yes	Yes	Yes
Observations	601,214	581,820	601,214	581,820
R-squared	0.0306	0.0026	0.0008	0.0025

Note. Robust standard errors are given in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

This suggests that promotional discounts in the 50–60% range represent a critical balance point: smaller discounts may not sufficiently motivate customers to trial and build trust, while excessively steep discounts risk devaluing the service and hindering the transition to sustained full-price adoption.

6. Heterogeneous Effects for Two Promotional Strategies

Building on Section 5, which establishes the distinct effectiveness of the two promotional strategies, we further examine how customers' behavioral inertia and their interaction with autonomous delivery vehicles moderate these main effects. Specifically, we conduct an exploratory analysis focusing on two critical dimensions: (i) habituation to the self-pickup model and (ii) encounters with delivery failure.

6.1. Heterogeneous Effects of Habituation to Self-Pickup Model

We first consider customer habituation to the self-pickup model. A higher degree of habituation may increase behavioral inertia against adopting autonomous delivery, thereby influencing the efficacy of the two promotional strategies. Since our sample consists of first-time autonomous delivery users who previously relied exclusively on self-pickup, their past pickup frequency serves as a suitable proxy for this habituation. Accordingly, we construct a binary variable, *High Self-Pickup Habituation*, which is set to 1 for customers whose volume of self-pickup packages in the year preceding our time window exceeds the median within their assigned treatment subgroup, and 0 otherwise.

6.1.1. Single-Stage Promotional Strategy We begin by examining how customer habituation to the self-pickup model influences the effectiveness of the single-stage strategy. For customers highly habituated to this traditional method, the strategy's limited benefits could be further diminished. These customers' high switching costs may render the first-order-free coupon insufficient for initial trials, thus weakening the intended positive trigger effect. Furthermore, even when customers with a strong preference for self-pickup are persuaded to trial the technology, their decision is more likely to be driven by the financial benefit rather than intrinsic interest, which presents two problems. First, it anchors customers to a reference price of zero, making subsequent full-price orders feel like a loss (Reimers and Xie 2019). Second, because customers attribute their trial to the external incentive rather than a shift in their underlying preferences, the single-stage offer does little to reduce their algorithm aversion. Consequently, these customers tend to redeem the offer without the intention of future engagement, increasing the risk of revenue cannibalization. With their underlying aversion remaining unchallenged, strongly habituated customers are also more likely to revert to self-pickup once the promotion ends, leading to worse long-term adoption outcomes.

To examine these effects, we introduce an interaction term, $Treatment \times$ *High Self-Pickup Habituation*, into our baseline model. The results in Table 8 reveal that the limited efficacy of the single-stage strategy diminishes significantly for customers with stronger habituation to the self-pickup mode. First, this strategy is less effective at encouraging an initial trial among these customers. As shown in Column (1), the coefficient of the interaction term for the number of daily autonomous delivery orders during the promotion is negative and statistically significant (β= -0.0018, $p <$ 0.001). This indicates that the positive trigger effect of the single-stage strategy is substantially weakened for habituated customers. For these individuals, a simple financial discount is insufficient to overcome their established habit. Second, this group also exhibits a more pronounced negative spillover effect. The statistically significant and negative coefficient of the interaction term in Column (3) (β= -0.0003, $p <$ 0.001) suggests that customers with stronger self-pickup habits are less likely to place full-price orders, thereby exacerbating revenue cannibalization. This pattern implies that these customers tend to view the offer as a one-time deal to be exploited rather than an opportunity to reassess the technology's value.

Lastly, the negative and statistically significant coefficients of the interaction term for the long-term analysis (Columns 2 and 4) reinforce this pattern (β = -0.0006, $p <$ 0.001), indicating a lower likelihood of sustained adoption after the promotion. While this promotional strategy is generally ineffective at fostering lasting adoption, its failure is particularly pronounced among customers with strong self-pickup habits. Taken together, these findings demonstrate that the single-stage strategy is not well-suited for overcoming strong behavioral inertia. For highly habituated customers, the limited effectiveness of this strategy is further undermined, resulting in worse adoption outcomes of autonomous delivery.

Table 8 Heterogeneous Effects of Self-Pickup Habituation for Single-Stage Strategy

	log(Num. of Orders)		*log(Num. of Full Price Orders)*	
Variables	*(1) Short (3.2-4.1)*	*(2) Long (4.2-5.1)*	*(3) Short (3.2-4.1)*	*(4) Long (4.2-5.1)*
$Treatment \times$ *High Self-Pickup Habituation*	-0.0018^{***}	-0.0006^{***}	-0.0003^{***}	-0.0006^{***}
	(0.0004)	(0.0002)	(0.0001)	(0.0002)
$Treatment$	0.0080^{***}	0.0002	-0.0009^{***}	0.0002
	(0.0003)	(0.0001)	(0.0001)	(0.0001)
Date Fixed Effects	Yes	Yes	Yes	Yes
Station Fixed Effects	Yes	Yes	Yes	Yes
Observations	726,919	703,470	726,919	703,470
R-squared	0.0042	0.0009	0.0011	0.0009

Note. Robust standard errors are given in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

6.1.2. Multi-Stage Promotional Strategy Nevertheless, the effectiveness of the multi-stage strategy is likely enhanced for customers strongly habituated to the self-pickup model. These two groups, low and high habituation, start from different psychological baselines, which determine the magnitude of this strategy's effect. For customers with low habituation, the primary barrier to adoption may be simple inertia. As this group is already psychologically proximate to trying autonomous delivery, the promotion may serve as a final nudge that activates a latent preference, resulting in a positive but incremental behavioral shift. Conversely, highly habituated customers tend to be psychologically distant from this new technology, as their ingrained self-pickup routine may create a significant cognitive barrier. The multi-stage strategy is particularly effective for this segment, as its structured sequence of low-risk, incentivized interactions is designed to dismantle this resistance. Each successful autonomous delivery provides direct, tangible evidence that counteracts their initial skepticism and fosters a rapid recalibration of trust (Lee and See 2004). Because these customers begin from a position of high resistance, the journey from aversion to adoption constitutes a more profound perceptual transformation. This greater psychological shift could translate into a larger marginal impact on autonomous delivery adoption, making the short- and long-term effects of the strategy more pronounced for this otherwise difficult-to-convert segment.

The results in Table 9 support this theory by demonstrating that the strategy's efficacy is amplified for strongly habituated customers across both short- and long-term horizons. First, this strategy generates significantly stronger short-term trigger and spillover effects for these customers. As detailed in Column (1), the coefficient of the interaction term is positive and statistically significant (β = 0.0056, $p < 0.001$), indicating that the lift in daily autonomous delivery orders during promotions is greater for more habituated customers. Furthermore, we find that the positive spillover effect of this promotional strategy is magnified for highly habituated individuals. The statistically significant and positive coefficient of the interaction term in Column (3) indicates that these customers are more likely to place full-price orders during the promotional period (β = 0.0009, $p < 0.01$). This finding suggests that the strategy does more than merely induce trial; it can recalibrate customers' value perception of autonomous vehicles. Therefore, for more habituated customers, this strategy appears to provide more powerful, tangible evidence that effectively dismantles their cognitive barriers and behavioral inertia, leading to a more rapid shift in preference.

Second, the short-term perceptual shift also translates into durable behavioral change. The positive and statistically significant coefficients in Columns (2) and (4) show that the long-term positive impact of the multi-stage strategy is greater for customers with stronger habituation to self-pickup ($p < 0.001$), which implies that the multi-stage strategy effectively converts the initial, incentivized trials into a sustained pattern of adoption for the resistant segment. By helping these customers overcome the cognitive barrier associated with their established routine, the strategy fosters a new, lasting behavioral pattern that favors autonomous delivery. In summary, these findings confirm that the efficacy of the multi-stage strategy is more pronounced for customers who are initially more habituated to the self-pickup model. This highlights the value of this

Table 9 Heterogeneous Effects of Self-Pickup Habituation for Multi-Stage Strategy

	log(*Num. of Orders*)		log(*Num. of Full Price Orders*)	
Variables	*(1) Short (3.2-4.1)*	*(2) Long (4.2-5.1)*	*(3) Short (3.2-4.1)*	*(4) Long (4.2-5.1)*
$Treatment \times$ *High Self-Pickup Habituation*	0.0056***	0.0020***	0.0009***	0.0019***
	(0.0004)	(0.0006)	(0.0003)	(0.0006)
$Treatment$	0.0369***	0.0040***	0.0001	0.0040***
	(0.0009)	(0.0004)	(0.0002)	(0.0004)
Date Fixed Effects	Yes	Yes	Yes	Yes
Station Fixed Effects	Yes	Yes	Yes	Yes
Observations	601,214	581,820	601,214	581,820
R-squared	0.0303	0.0026	0.0009	0.0025

Note. Robust standard errors are given in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

strategy not merely as a promotional tool, but as a targeted and structured behavioral intervention capable of converting this challenging customer segment into sustained, full-price adopters.

6.2. Heterogeneous Effects of Delivery Failure

Next, we examine how delivery failure, defined as instances where a customer does not retrieve their package from autonomous vehicles during the scheduled delivery time slot, moderates the effectiveness of single-stage and multi-stage promotional strategies. To capture this effect, we measure the log-transformed cumulative number of delivery failures experienced by each first-time customer prior to the focal day, denoted as $log(No.\ of\ Delivery\ Failure)$.

6.2.1. Single-Stage Promotional Strategy

We begin by examining how the effectiveness of the single-stage strategy depends on the delivery performance of autonomous delivery technology. A delivery failure can serve as a salient negative reinforcement (Gelbrich 2010, Xie et al. 2024), providing customers with concrete evidence that validates their skepticism toward autonomous delivery. Instead of fostering a positive, low-risk trial experience, a delivery failure might turn the promotion into a frustrating event (Anderson et al. 2009), giving customers a clear reason to question the technology's value at full price. This confirmation of unreliability heightens customer reluctance to place subsequent full-price orders, thereby amplifying the negative short-term spillover effect and weakening the positive trigger effect of this strategy.

To examine the role of delivery failures, we extend the baseline Equation (1) by incorporating an interaction term $Treatment \times$ *log(No. of Delivery Failure)*. The results in Table 10 suggest a pattern where delivery failures erode the limited benefits of the single-stage strategy. For the short-term trigger effect in Column (1), we observe a statistically significant and negative coefficient of the interaction term (β = -0.0213, $p <$ 0.001). This indicates that with each delivery failure, the efficacy of the first-time-free incentive to induce a trial diminishes, as the negative experience could counteract the appeal of the financial discount. Similarly, for the short-term cannibalization effect in Column (3), the coefficient of the interaction term is again statistically significant and negative (β = -0.0271, $p <$ 0.001), which suggests that delivery failures may increase customer reluctance to make subsequent full-price purchases by reinforcing perceptions of unreliability.

Regarding the long-term analysis, the coefficients of the interaction term in Columns (2) and (4) are negative and statistically significant ($\beta = -0.0333$, $p < 0.001$). Although our main results in Section 5.1 demonstrate that the single-stage strategy fails to generate lasting adoption, these findings highlight that delivery failures can even exacerbate this long-term ineffectiveness. In summary, while the single-stage strategy alone is insufficient to build trust, its limited benefits are further compromised following delivery failures.

Table 10 Heterogeneous Effects of Delivery Failure for Single-Stage Strategy

	log(*Num. of Orders*)		log(*Num. of Full Price Orders*)	
Variables	*(1) Short (3.2-4.1)*	*(2) Long (4.2-5.1)*	*(3) Short (3.2-4.1)*	*(4) Long (4.2-5.1)*
$Treatment \times$ *log(No. of Delivery Failure)*	-0.0213^{***}	-0.0333^{***}	-0.0271^{***}	-0.0333^{***}
	(0.0080)	(0.0052)	(0.0075)	(0.0052)
$Treatment$	0.0071^{***}	-0.0000	-0.0011^{***}	-0.0001
	(0.0002)	(0.0001)	(0.0001)	(0.0001)
log(No. of Delivery Failure)	0.0273^{***}	0.0346^{***}	0.0274^{**}	0.0346^{***}
	(0.0074)	(0.0052)	(0.0075)	(0.0052)
Date Fixed Effects	Yes	Yes	Yes	Yes
Station Fixed Effects	Yes	Yes	Yes	Yes
Observations	726,919	703,470	726,919	703,470
R-squared	0.0043	0.0020	0.0016	0.0020

Note. Robust standard errors are given in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

6.2.2. Multi-Stage Promotional Strategy In contrast to the single-stage offer, the multi-stage promotional strategy's short-term trigger effect might exhibit greater resilience to delivery failures, largely due to the tangible reward of repeated discounts. The sequence of financial incentives may create a low-risk environment in which customers are willing to try again despite a prior negative outcome. However, such resilience is unlikely to extend to the deeper mechanisms necessary for durable behavioral change (Kanuri and Andrews 2019). Each failed delivery provides concrete, negative evidence that might undermine the trust and perceived utility accumulated from previous successful experiences. This disruption could weaken the positive short-term spillover effect, as customers who encounter unreliability could be hesitant to pay full price when their confidence in the technology has been damaged. Moreover, these failures may be an obstacle to the conversion of experience-based trust into a lasting habit. Instead of mitigating algorithm aversion, negative experiences could instead reinforce this bias by validating customers' initial skepticism. As a result, behavioral change is less likely to persist once price promotions end, weakening the long-term adoption of autonomous delivery.

The results in Table 11 support this nuanced view. First, for the trigger impact, we observe a negative but statistically insignificant coefficient of the interaction term in Column (1), which suggests that the continuous offer of coupons could provide a temporary buffer against the shock of a negative experience. Unlike customers in the single-stage group, those in the multi-stage group are less likely to immediately stop ordering after a poor experience, as the presence of future coupons may motivate them to give the technology another try. However, while customers may continue to use coupons after a failure, their willingness to pay full price might be lower. As shown in Column (3), the coefficient of the interaction term for full-price orders during this period is statistically significant and negative ($\beta = -0.0232$, $p < 0.001$). This result suggests that the negative experience could dampen the positive spillover effect, possibly by interrupting the process of building familiarity and trust.

The cost associated with a delivery failure also extends to the post-promotional period. Columns (2) and (4) show that the coefficient of the interaction term is negative and statistically significant for long-term specifications ($p < 0.001$), which indicates that the short-term resilience does not translate into durable adoption. A delivery failure appears to leave a lasting negative impression that hinders the conversion of repeated trials into habitual, full-price adoption. Once the financial incentives are removed, customers who experienced failures are significantly less likely to continue using the technology.

Overall, these findings demonstrate that the multi-stage strategy does not render the autonomous delivery technology immune to delivery failures. In the presence of such failures, coupons may function less as an effective tool for building trust and more as mere compensation for the perceived risk of an unreliable technology. This highlights a vital observation: promotional incentives cannot compensate for operational errors.

Table 11 Heterogeneous Effects of Delivery Failure for Multi-Stage Strategy

	log(*Num. of Orders*)		log(*Num. of Full Price Orders*)	
Variables	*(1) Short (3.2-4.1)*	*(2) Long (4.2-5.1)*	*(3) Short (3.2-4.1)*	*(4) Long (4.2-5.1)*
$Treatment \times$ *log(No. of Delivery Failure)*	−0.0112	-0.0214^{***}	-0.0232^{***}	-0.0217^{***}
	(0.0091)	(0.0057)	(0.00076)	(0.0057)
$Treatment$	0.0393^{***}	0.0045^{***}	0.0004^{***}	0.0044^{***}
	(0.0007)	(0.0003)	(0.0002)	(0.0003)
log(No. of Delivery Failure)	0.0268^{***}	0.0345^{***}	0.0273^{***}	0.0345^{***}
	(0.0074)	(0.0052)	(0.00075)	(0.0052)
Date Fixed Effects	Yes	Yes	Yes	Yes
Station Fixed Effects	Yes	Yes	Yes	Yes
Observations	601,214	581,820	601,214	581,820
R-squared	0.0303	0.0039	0.0013	0.0038

Note. Robust standard errors are given in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

7. Robustness Checks

This section presents a series of empirical tests to evaluate the validity and robustness of our main findings. First, we vary the activity threshold used to define our customer sample. Second, we employ a 2SLS approach to estimate the average treatment effect. Third, we allow for two-way clustering of standard errors by customer and date. Fourth, we adopt three alternative measures of technology adoption as the dependent variable. Fifth, we re-estimate the long-term effect using two alternative empirical analyses. Sixth, we implement two additional analyses to validate the negative short-term spillover effect. Seventh, we re-run our main analysis using weekly aggregated data.

7.1. Alternative Prior Package Volume Thresholds

In our main analysis, our sample consists of first-time autonomous delivery customers who had received at least one package in the year preceding the study. This criterion ensures that the analysis focuses on existing customers who are familiar with the platform but have so far refrained from using autonomous delivery, allowing us to capture potential reluctance toward the new technology. As a robustness check, we test the sensitivity of our results to this threshold by re-estimating our models on subsamples of customers with higher levels of prior engagement, specifically, those who had received at least 5, 10, or 15 packages in the preceding year. These varying thresholds not only test the stability of our findings but also proxy for customers' baseline familiarity with traditional delivery services and, consequently, their potential reluctance to adopt autonomous delivery technology.

The results from these more constrained samples remain highly consistent with our main findings. As detailed in Tables A.3, A.4, and A.5 in the Appendix, this consistency holds for both short- and long-term effects across all main analyses (i.e., for the overall sample, the single-stage strategy, and the multi-stage strategy). These findings indicate that our results are not driven by a particular segment of low- or high-frequency users; rather, the promotional effects hold consistently across customers with varying levels of prior engagement.

7.2. Robustness Check on Average Treatment Effects for Short-Term Analysis

Our main analysis estimates the intention-to-treat (ITT) effect, which measures the causal impact of being offered price promotions, regardless of whether they are redeemed. The ITT is the most appropriate measure for evaluating the overall effectiveness of the promotion program itself. However, from a practical standpoint, it is also important to understand the effect of actually using the coupon. A simple comparison between users and non-users might be misleading due to self-selection bias, as customers who choose to redeem coupons may be inherently more price-sensitive or curious about the technology.

To address this, we employ a 2SLS approach to estimate the Average Treatment Effect (ATE) of coupon usage. We use the random assignment to the treatment group as the instrument variable for the endogenous variable of actual coupon redemption (Angrist and Pischke 2009). For this approach to be valid, two key assumptions must hold. First, the relevance assumption is met because the random offer of a promotion is, by design, a significant and direct predictor of coupon redemption. Second, the crucial exclusion restriction is satisfied: random assignment affects customer behavior only through the channel of coupon redemption. This holds because customers in the treatment and control groups were otherwise identical and did not receive other differential treatments or marketing messages during our time window, as confirmed in Section 3.2. This method allows us to pinpoint the causal effect of coupon use for the subsample of customers who are induced to try the technology by the promotion. The results from the 2SLS estimation, presented in Tables A.6, A.7, and A.8 in the Appendix, are consistent with our main ITT analysis across all customer groups and for both the single- and multi-stage strategies. This consistency confirms that the observed behavioral changes are a direct consequence of experiencing autonomous delivery via the promotion, thereby strengthening our causal inference.

7.3. Clustered Standard Errors

Our panel dataset, which contains repeated observations for each customer over time, may introduce complex dependencies in the error terms (Wang and Overby 2023, Forderer et al. 2025). Specifically, the standard errors of our estimates may be biased due to (1) serial correlation for a given customer across time and (2) cross-sectional correlation across customers due to common shocks on a given date. Failing to account for both sources of correlation might underestimate the standard errors and inflate the statistical significance of our findings.

To ensure our inference is robust, we re-estimate our main models using two-way clustered standard errors at the customer and date levels. This approach allows for arbitrary correlation in the residuals both within each customer over time and within each date across all customers, thereby simultaneously addressing both potential issues. The results, presented in Panels A, B, and C of Table A.9 in the Appendix, show that our findings are robust to this more conservative specification. The short-term and long-term estimates remain statistically significant and quantitatively similar to our main findings across all models (i.e., for the overall sample, single-stage strategy, and multi-stage strategy). These consistent results provide additional evidence that our findings are not an artifact of understated standard errors and are robust to both serial and cross-sectional dependence.

7.4. Alternative Dependent Variables

The main dependent variable in our analysis is the number of daily autonomous delivery orders, which captures changes in ordering frequency. To ensure our findings are not specific to this single metric, we examine three alternative outcome variables that capture different facets of customer adoption.

First, we re-estimate our model using the raw autonomous delivery order count (without logarithmic transformation), and the corresponding results for the overall sample, the single-stage strategy, and the multi-stage strategy are provided in Panels A, B, and C of Table A.10 in the Appendix. Second, we use a binary dependent variable indicating whether a customer placed at least one autonomous delivery order on a given day, isolating the effect on the extensive margin of adoption. The results for this analysis are presented in Table A.11 in the Appendix for the overall sample, the single-stage strategy, and the multi-stage strategy. Third, we measure the percentage of autonomous delivery orders among a customer's total package orders, which captures the shift in preference toward the autonomous delivery option. The corresponding results are shown in Table A.12 in the Appendix. The results using these alternative dependent variables closely align with our prior main findings, providing additional support for our conclusions.

7.5. Robustness Checks on Long-Term Effects

In this section, we conduct two additional analyses to validate our findings on the long-term analysis. We first address the potential carryover effects from the promotion. Because next-day scheduling could cause coupon-induced orders to be fulfilled on April 2—the first day of the post-treatment period—we exclude all observations from that date to keep the post-promotion period uncontaminated. We then re-estimate our models on this restricted sample and obtain the results in Table A.13 in the Appendix, which closely align with our main findings.

Second, to further ensure the robustness of our findings on long-term effects, we employ an alternative econometric specification: the Cox proportional hazards model. This survival analysis approach allows us to model the timing of customer adoption in the post-promotion period, rather than the aggregate number of orders. Specifically, we examine the hazard rate, the conditional probability of a customer placing their first full-price autonomous delivery order at a given time. This provides a more dynamic perspective on how the promotions influenced the speed of un-incentivized adoption. The results, presented as hazard ratios in Table A.14 in the Appendix, corroborate our main findings. Overall, the promotion significantly accelerated long-term adoption, increasing the rate by approximately 50% ($HR = 1.5078$, $p < 0.001$) compared to the control group.

However, this aggregate effect masks a critical divergence between the two promotional strategies. The single-stage strategy has no statistically significant impact on the long-term adoption rate ($HR = 1.0883$, $p > 0.1$), aligning with our finding that it fails to create a lasting behavioral change. In contrast, the multi-stage strategy increased the adoption rate by 148% ($HR = 2.4759$, $p < 0.001$), making customers almost 2.5 times more likely to place their first un-incentivized order at any given point. This finding provides additional evidence that the multi-stage design effectively fosters a durable habit. In summary, the findings from both analyses provide consistent evidence that the multi-stage strategy can convert initial trials into long-term adoption, whereas the single-stage strategy does not.

7.6. Robustness Checks on Short-Term Cannibalization Effects

Our main analysis reveals a negative short-term spillover effect for both the overall promotion and the single-stage strategy, suggesting revenue cannibalization. This finding, however, may be subject to two alternative interpretations. In this section, we conduct two additional analyses to address these concerns.

The first potential concern is that the observed negative spillover is driven by customers in the single-stage strategy who redeem the first-time-free coupon but have no subsequent packages, thus having no opportunity to place a full-price order. The inclusion of these customers, who, by definition, place zero full-price orders after coupon redemption, may mechanically contribute to a negative spillover and overstate the true level of cannibalization. To address this concern, we replicate our analysis excluding this customer segment. The results, shown in Table A.15 in the Appendix, are nearly identical to our main estimates.

This confirms that the negative spillover effect is not merely a statistical artifact of this group but reflects a sustained reduction in full-price orders among treated customers.

Another potential issue with our observed negative spillover effect may be an artifact of our measurement rather than a true behavioral response. Specifically, when customers in the treatment group redeem a coupon, that order is by definition not a full-price order. This mechanically reduces the number of available packages for using autonomous delivery at full price for treated customers compared to the control group, potentially creating a downward bias in the estimate for spillover effects. While our main dependent variables serve as direct measures of firms' revenue from autonomous delivery technology, this potential concern warrants further investigation. To more precisely pinpoint a sustained behavioral spillover, we conduct another analysis. Specifically, we exclude all customer-day observations on which coupons are actually redeemed. For the remaining days, we re-evaluate the spillover effect using the proportion of full-price autonomous delivery orders among a customer's total package orders as the dependent variable. This more stringent approach ensures we measure customers' propensity to choose a full-price autonomous delivery on days when they are not using a promotional offer, thereby removing the direct and mechanical impact of coupon redemption from the analysis.

The results in Table A.16 in the Appendix remain highly consistent with our main findings. We continue to observe a negative and statistically significant coefficient for both the overall treatment group and the single-stage strategy subgroup. This robust finding confirms that the negative spillover is not simply an artifact of coupon usage. Instead, it reflects a broader strategic behavior wherein customers in the single-stage strategy group become less inclined to place full-price orders throughout the promotional period.

Together, these analyses strengthen the robustness of our conclusion regarding short-term cannibalization. We note that this robustness check is unnecessary for the multi-stage strategy, as its positive spillover effect already indicates increased customer engagement rather than cannibalization.

7.7. Analysis of Weekly-Aggregated Data

Our main analysis, conducted at the customer daily level, leverages the high-frequency and individual-level granularity of our data. To ensure the robustness of our findings and offer a broader perspective, we re-estimate our main models using a weekly aggregation. This approach helps address potential noise from high-frequency fluctuations and capture a more stable trend in customer adoption of autonomous delivery. The results from our weekly analysis, presented in Panels A, B, and C of Table A.17 in the Appendix, are highly consistent with our main findings. This consistency holds for both short- and long-term analyses across all main analyses (i.e., the overall sample, single-stage strategy, and multi-stage strategy).

8. Concluding Remarks

AI technologies, from autonomous delivery vehicles in last-mile logistics to algorithms in financial forecasting, are increasingly surpassing human experts in domains once thought to require uniquely human judgment. Yet, their widespread adoption is often constrained by a persistent psychological barrier: algorithm aversion. Overcoming this reluctance and motivating skeptical customers to trial and adopt novel AI solutions has therefore become a central challenge for businesses and innovators. While prior research has largely emphasized system-based interventions aimed at building user trust (Dietvorst et al. 2018, Reich et al. 2023), one of the most established tools in business practice, price promotions, has received little attention in this setting. Whether financial incentives can help overcome deep-seated psychological barriers like algorithm aversion remains an open question. Furthermore, while firms often rely on either single-stage or multi-stage promotional strategies, their distinct psychological consequences for AI adoption decisions are not well understood. To address these gaps, we conducted a large-scale field experiment in collaboration with a leading global e-commerce platform, in which we randomly assigned coupons to existing platform users who had never used autonomous delivery vehicles.

Our results reveal a critical tension in the use of price promotions to combat algorithm aversion. While promotions can trigger initial trials, they do so at the cost of cannibalizing short-term, full-price sales. Taken in isolation, this trade-off might suggest that promotions are an ineffective tool. However, our long-term analysis shows that treated customers who received promotions are more likely to develop a habit of using autonomous delivery at full price after the incentives end. This demonstrates that promotions could extend beyond driving the immediate transaction.

Motivated by the above potential conflicting findings, we next focus on the promotional design. We find that the single-stage strategy is a myopic tactic. While it triggers a trial, this approach causes revenue cannibalization and, crucially, fails to produce the long-term behavioral change. By framing the interaction as purely transactional, it merely rents a customer for a single order. In contrast, the multi-stage strategy emerges as an effective tool for durable behavioral change. By encouraging repeated, low-risk interactions, it not only drives significantly more trials but also generates a positive short-term spillover effect, as increased familiarity reshapes customer perception of autonomous delivery. More importantly, it fosters a long-term habit, proving that a sustained campaign is instrumental in converting hesitant users into durable adopters. Furthermore, the effectiveness of a multi-stage strategy is related to its promotional frequency and intensity, both of which follow an inverted U-shaped relationship with customer adoption.

Delving deeper, our heterogeneous analyses identify the patterns behind these divergent outcomes. Customer habituation to self-pickup, for instance, could diminish the limited benefits of the single-stage strategy, as this simple incentive is insufficient to overcome this behavioral inertia. Conversely, the effectiveness of the multi-stage strategy is amplified for customers habituated to self-pickup, as this approach is particularly effective at dismantling cognitive barriers and converting this habituated segment to full-price adopters. Additionally, our results highlight that delivery failures are correlated with worse outcomes of both strategies. While the multi-stage strategy provides a degree of short-term resilience, negative experiences ultimately negate its positive spillover effect and inhibit long-term habit formation.

Our study makes several contributions to theory and practice. First, we move beyond cognitive and design-based interventions typically studied in lab settings (Burton et al. 2020, Jussupow et al. 2020). Instead, we introduce and causally validate price promotions as a scalable behavioral intervention that mitigates algorithm aversion in a real-world context. Our key insight is that overcoming such a deep-seated bias is not about a single interaction but a structured process. A one-off incentive is ineffective because customers attribute their trial to an external cause, leaving their underlying bias unchallenged. In contrast, a multi-stage strategy fosters a gradual process of familiarization, where repeated, low-risk interactions provide tangible evidence needed to dismantle abstract fears, build trust, and internalize a sustained preference for the technology. This adds a crucial temporal and process-oriented dimension to understanding how to overcome algorithm aversion.

Second, we demonstrate that the design of promotions triggers different and even opposing psychological pathways, an area underexplored in prior research. While previous research on price promotions often weighs economic benefits (e.g., sales lift) against their costs (e.g., heightened price sensitivity) (Reimers and Xie 2019, Zhang et al. 2020), we reveal a more nuanced dynamic. Our findings demonstrate a sharp divergence between a transactional pathway (single-stage), which lowers price expectation and cannibalizes full-price demand, and a familiarization pathway (multi-stage). This latter path can generate positive spillovers and build lasting habits even after promotions conclude. This introduces an important strategic dimension, showing that promotions are not merely economic instruments but designed experiences that can either rent transactional behavior or cultivate sustained preference shifts.

Third, moving beyond the downstream consequences of AI use (Xu et al. 2024, Sun et al. 2025), we address the critical, yet often-overlooked, upstream challenge of securing initial user adoption. Business practice frequently assumes that once an advanced AI tool is introduced, users will naturally engage with it. Our study challenges this assumption by providing a causal framework for guiding the user's journey from aversion to habitual use. We demonstrate that successful AI deployment is not merely a technical problem but a socio-technical hurdle that requires carefully designed psychological nudges to bridge the human-algorithm trust gap. By identifying the specific promotional architecture that fosters this trust, our work offers a concrete blueprint for translating the latent technological potential of AI systems into realized economic and social value.

From a managerial perspective, our findings offer actionable guidelines for overcoming the adoption hurdles of novel AI technologies. First, managers should avoid relying on simple, one-off deep discounts. While such promotions can generate the initial trial, this approach might be a value-destructive trap. It triggers a transactional mindset, attracting customers for a single use rather than building the trust necessary for long-term adoption. Instead, we recommend that managers design sustained, multi-stage promotional campaigns that function as a guided onboarding process. This approach transforms promotions from simple financial incentives into structured pathways for building familiarity and trust with the technology. Consequently, the goal shifts from winning a single sale to fostering long-term user adoption.

Our findings also provide data-backed and clear insights for setting the parameters of the multi-stage strategy. An effective interval between promotional offers may be roughly two weeks, with average discounts of 50–60%. This framework could strike a crucial balance between motivating trials and preserving the technology's perceived value, thereby allowing managers to maximize their return on promotional investment. Finally, managers need to be aware that promotions cannot compensate for a negative user experience. Our study shows that negative experiences, such as delivery failures, erode the trust that promotions are meant to build. Although the multi-stage strategy can entice a customer to try again, it is incapable of erasing the memory of the past failure or building durable adoptions on a foundation of unreliable service. Therefore, promotional spending is rendered ineffective if the AI technology does not consistently deliver on its promise.

While this study offers new insights into how price promotions can mitigate customer algorithm aversion in the context of autonomous delivery, it has several limitations that present avenues for future research. First, our experiment is conducted on university campuses, where users may be more tech-savvy or price-sensitive than the general population. Future research can test the generalizability of our findings in other demographic contexts (e.g., suburban households) and other AI applications with different risk profiles, such as medical diagnostic tools or financial robo-advisors, where the psychological barriers may be more pronounced. Second, our analysis focuses on the single-stage and multi-stage promotional strategies. Future work can investigate other common approaches, such as bundling the AI service with other products, implementing a loyalty program, or exploring non-monetary incentives like access to premium features. Comparing these alternatives would yield a more comprehensive framework for managers. Third, this study deliberately focuses on first-time users to examine the effect on initial algorithm aversion. A crucial next step is to investigate how these promotional strategies impact experienced users. For instance, future studies can explore whether a multi-stage promotion deepens engagement and prevents churn among existing users or triggers customers to expect continued discounts. Fourth, our study infers trust from adoption outcomes instead of measuring it directly. Future research can incorporate established psychometric scales (e.g., via surveys) to measure trust explicitly, thereby further validating our proposed trust-building mechanism.

In conclusion, our study demonstrates that price promotions can be an effective tool for overcoming algorithm aversion, but their effectiveness is critically dependent on their design. A single, deep discount could foster a transactional mindset that fails to cultivate lasting adoption. In contrast, a multi-stage promotional strategy transforms the incentive from a simple financial transaction into an effective catalyst for behavioral change. By encouraging repeated interactions, this approach enables users to dismantle their initial apprehension, build trust, and ultimately internalize the technology as a valuable habit. Thus, our research provides a scalable blueprint for practitioners, showing that the strategic deployment of promotions can bridge the critical gap between technological potential and widespread user acceptance, paving the way for the successful integration of AI into daily life.

References

Allen, Ryan, Prithwiraj Choudhury. 2022. Algorithm-augmented work and domain experience: The countervailing forces of ability and aversion. *Organization Science* **33**(1) 149–169.

Anderson, Eric T, Edward J Fox. 2019. How price promotions work: A review of practice and theory. *Handbook of the Economics of Marketing* **1** 497–552.

Anderson, Eric T, Duncan I Simester. 2004. Long-run effects of promotion depth on new versus established customers: Three field studies. *Marketing Science* **23**(1) 4–20.

Anderson, Shannon W, L Scott Baggett, Sally K Widener. 2009. The impact of service operations failures on customer satisfaction: Evidence on how failures and their source affect what matters to customers. *Manufacturing & Service Operations Management* **11**(1) 52–69.

Angrist, Joshua D, Jörn-Steffen Pischke. 2009. *Mostly harmless econometrics: An empiricist's companion*. Princeton University Press.

Arora, Neeraj, Ty Henderson. 2007. Embedded premium promotion: Why it works and how to make it more effective. *Marketing Science* **26**(4) 514–531.

Aseri, Manmohan, Amit Mehra, Vijay Mookerjee, Hong Xu. 2024. Should an Ad agency offer geoconquesting or protection from it? *Information Systems Research* **35**(2) 850–870.

Bailey, Michael, Drew Johnston, Theresa Kuchler, Johannes Stroebel, Arlene Wong. 2022. Peer effects in product adoption. *American Economic Journal: Applied Economics* **14**(3) 488–526.

Berente, Nicholas, Bin Gu, Jan Recker, Radhika Santhanam. 2021. Managing artificial intelligence. *MIS Quarterly* **45**(3).

Bockstedt, Jesse C, Joseph R Buckman. 2025. Humans' use of AI assistance: The effect of loss aversion on willingness to delegate decisions. *Management Science, Forthcoming* .

Brynjolfsson, Erik, Xiang Hui, Meng Liu. 2019. Does machine translation affect international trade? Evidence from a large digital platform. *Management Science* **65**(12) 5449–5460.

Burton, Jason W, Mari-Klara Stein, Tina Blegind Jensen. 2020. A systematic review of algorithm aversion in augmented decision making. *Journal of Behavioral Decision Making* **33**(2) 220–239.

Cadario, Romain, Chiara Longoni, Carey K Morewedge. 2021. Understanding, explaining, and utilizing medical artificial intelligence. *Nature Human Behaviour* **5**(12) 1636–1642.

Castelo, Noah, Maarten W Bos, Donald R Lehmann. 2019. Task-dependent algorithm aversion. *Journal of Marketing Research* **56**(5) 809–825.

Cowgill, Bo, Catherine E Tucker. 2020. Economics, fairness and algorithmic bias. *Available at SSRN 3361280* .

Dargnies, Marie-Pierre, Rustamdjan Hakimov, Dorothea Kübler. 2024. Aversion to hiring algorithms: Transparency, gender profiling, and self-confidence. *Management Science, Forthcoming* .

DelVecchio, Devon, H Shanker Krishnan, Daniel C Smith. 2007. Cents or percent? The effects of promotion framing on price expectations and choice. *Journal of Marketing* **71**(3) 158–170.

Dietvorst, Berkeley J, Soaham Bharti. 2020. People reject algorithms in uncertain decision domains because they have diminishing sensitivity to forecasting error. *Psychological Science* **31**(10) 1302–1314.

Dietvorst, Berkeley J, Joseph P Simmons, Cade Massey. 2015. Algorithm aversion: People erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology: General* **144**(1) 114.

Dietvorst, Berkeley J, Joseph P Simmons, Cade Massey. 2018. Overcoming algorithm aversion: People will use imperfect algorithms if they can (even slightly) modify them. *Management Science* **64**(3) 1155–1170.

Erdem, Tülin, Baohong Sun. 2002. An empirical investigation of the spillover effects of advertising and sales promotions in umbrella branding. *Journal of Marketing Research* **39**(4) 408–420.

Fang, Zhen, Yi-Chun Ho, Xue Tan, Yong Tan. 2021. Show me the money: The economic impact of membership-based free shipping programs on e-tailers. *Information Systems Research* **32**(4) 1115–1127.

Fong, Nathan, Yuchi Zhang, Xueming Luo, Xiaoyi Wang. 2019. Targeted promotions on an e-book platform: Crowding out, heterogeneity, and opportunity costs. *Journal of Marketing Research* **56**(2) 310–323.

Forderer, Jens, Dominik Gutt, Brad N Greenwood. 2025. Star wars: An empirical study of star performer turnover and content supply on multisided streaming platforms. *Information Systems Research* .

Gardner, Benjamin, Amanda L Rebar. 2019. Habit formation and behavior change. *Oxford Research Encyclopedias of Psychology*.

Gelbrich, Katja. 2010. Anger, frustration, and helplessness after service failure: Coping strategies and effective informational support. *Journal of the Academy of Marketing Science* **38**(5) 567–585.

George, Mailys M, Sarah Wittman, Kevin W Rockmann. 2022. Transitioning the study of role transitions: From an attribute-based to an experience-based approach. *Academy of Management Annals* **16**(1) 102–133.

Ghose, Anindya, Heeseung Andrew Lee, Kihwan Nam, Wonseok Oh. 2024. The effects of pressure and self-assurance nudges on product purchases and returns in online retailing: Evidence from a randomized field experiment. *Journal of Marketing Research* **61**(3) 517–535.

Greiner, Ben, Philipp Grünwald, Thomas Lindner, Georg Lintner, Martin Wiernsperger. 2025. Incentives, framing, and reliance on algorithmic advice: An experimental study. *Management Science, Forthcoming* .

Guo, Yingyu, Ting Li. 2025. Algorithm aversion in green consumption .

Han, Elizabeth, Dezhi Yin, Han Zhang. 2023. Bots with feelings: should AI agents express positive emotion in customer service? *Information Systems Research* **34**(3) 1296–1311.

Hao, Shuai, Yuqian Xu. 2025. Voice chatbot design: Leveraging the preemptive prediction algorithm. *Available at SSRN 5216183* .

Jussupow, Ekaterina, Izak Benbasat, Armin Heinzl. 2020. Why are we averse towards algorithms? A comprehensive literature review on algorithm aversion .

Kahneman, Daniel, Amos Tversky. 1979. Prospect theory: An analysis of decision under risk. *Econometrica* **47**(2) 363–391.

Kanuri, Vamsi K, Michelle Andrews. 2019. The unintended consequence of price-based service recovery incentives. *Journal of Marketing* **83**(5) 57–77.

Kawaguchi, Kohei. 2021. When will workers follow an algorithm? A field experiment with a retail business. *Management Science* **67**(3) 1670–1695.

Klenow, Peter J, Benjamin A Malin. 2010. Microeconomic evidence on price-setting. *Handbook of Monetary Economics*, vol. 3. Elsevier, 231–284.

Ko, Ga Young, Donghyuk Shin, Seigyoung Auh, Yeonjung Lee, Sang Pil Han. 2023. Learning outside the classroom during a pandemic: Evidence from an artificial intelligence-based education app. *Management Science* **69**(6) 3616–3649.

KPMG. 2023. Trust in artificial intelligence. URL `https://kpmg.com/xx/en/our-insights/ai-and-technology/trust-in-artificial-intelligence.html`.

Kumar, Anuj, Amit Mehra. 2024. Improving educational delivery in K-12 schools with personalization: Evidence from a randomized field experiment in India. *Available at SSRN 2756059* .

Lee, David S, Justin McCrary, Marcelo J Moreira, Jack Porter. 2022. Valid t-ratio inference for IV. *American Economic Review* **112**(10) 3260–3290.

Lee, John D, Katrina A See. 2004. Trust in automation: Designing for appropriate reliance. *Human Factors* **46**(1) 50–80.

Lee, Lynne, Vincent Charles. 2021. The impact of consumers' perceptions regarding the ethics of online retailers and promotional strategy on their repurchase intention. *International Journal of Information Management* **57** 102264.

Li, Chunxiao, Hongchang Wang, Songtao Jiang, Bin Gu. 2024. The effect of AI-enabled credit scoring on financial inclusion: Evidence from one million underserved population. *MIS Quarterly, Forthcoming* .

Liang, Chen, Zhuoyan Li, Ming Yin. 2025a. AI disclosure and content evaluation. *Available at SSRN 5229489* .

Liang, Chen, Jing Peng, Zhuoyan Li, Ming Yin. 2025b. The valuation of generative AI in content creation: Evidence from gig workers. *Available at SSRN 4825716* .

Liu, Meng, Xiaocheng Tang, Siyuan Xia, Shuo Zhang, Yuting Zhu, Qianying Meng. 2025. Algorithm aversion: Evidence from ridesharing drivers. *Management Science, Forthcoming* .

Luo, Xueming, Siliang Tong, Zheng Fang, Zhe Qu. 2019. Frontiers: Machines vs. humans: The impact of artificial intelligence chatbot disclosure on customer purchases. *Marketing Science* **38**(6) 937–947.

Lysyakov, Mikhail, Siva Viswanathan. 2023. Threatened by AI: Analyzing users' responses to the introduction of AI in a crowd-sourcing platform. *Information Systems Research* **34**(3) 1191–1210.

Mani, Zied, Inès Chouk. 2018. Consumer resistance to innovation in services: Challenges and barriers in the internet of things era. *Journal of Product Innovation Management* **35**(5) 780–807.

Mejia, Jorge, Anandasivam Gopal, Michael Trusov. 2020. Deal or no deal? Online deals, retailer heterogeneity, and brand evaluations in a competitive environment. *Information Systems Research* **31**(4) 1087–1106.

Ni, Xiao, Yiwei Wang, Tianjun Feng, Lauren Xiaoyuan Lu, Yitong Wang, Congyi Zhou. 2025. Generative AI in action: Field experimental evidence on worker performance in E-Commerce customer service operations. *Available at SSRN 5012601* .

Nijs, Vincent R, Marnik G Dekimpe, Jan-Benedict EM Steenkamps, Dominique M Hanssens. 2001. The category-demand effects of price promotions. *Marketing Science* **20**(1) 1–22.

Pauwels, Koen, Dominique M Hanssens, Sivaramakrishnan Siddarth. 2002. The long-term effects of price promotions on category incidence, brand choice, and purchase quantity. *Journal of Marketing Research* **39**(4) 421–439.

Reich, Taly, Alex Kaju, Sam J Maglio. 2023. How to overcome algorithm aversion: Learning from mistakes. *Journal of Consumer Psychology* **33**(2) 285–302.

Reimers, Imke, Claire Xie. 2019. Do coupons expand or cannibalize revenue? Evidence from an e-market. *Management Science* **65**(1) 286–300.

Rusak, Gili, Benjamin S Manning, John J Horton. 2025. AI agents can enable superior market designs .

Schanke, Scott, Gordon Burtch, Gautam Ray. 2021. Estimating the impact of "humanizing" customer service chatbots. *Information Systems Research* **32**(3) 736–751.

Su, Yi, Kaiyu Zhang, Qili Wang, Liangfei Qiu. 2023. Generative AI and human knowledge sharing: Evidence from a natural experiment. *Available at SSRN 4628786* .

Sun, Chenshuo, Zijun Shi, Xiao Liu, Anindya Ghose. 2025. The effect of voice AI on digital commerce. *Information Systems Research* **36**(2) 1147–1166.

Sun, Shujing, Lauren Xiaoyuan Lu, Susan F Lu, Wei Gu. 2024. When peers matter more: The dominance of social influence over algorithm accuracy in patient decision making. *Available at SSRN 4966406* .

Thaler, Richard H, Cass R Sunstein. 2009. *Nudge: Improving decisions about health, wealth, and happiness*. Penguin.

Vaidya, Avinash Rao, Johanny Castillo, Alejandro Torres, David Badre. 2025. Influences of familiarity and recollection on value-based decision-making. *PLoS One* **20**(5) e0322632.

Van den Broek, Elmira, Anastasia Sergeeva, Marleen Huysman. 2021. When the machine meets the expert: An ethnography of developing AI for hiring. *MIS Quarterly* **45**(3) 1557–1580.

Verplanken, Bas, Henk Aarts. 1999. Habit, attitude, and planned behaviour: Is habit an empty construct or an interesting case of goal-directed automaticity? *European Review of Social Psychology* **10**(1) 101–134.

Wang, Hanchen, Tianfan Fu, Yuanqi Du, Wenhao Gao, Kexin Huang, Ziming Liu, Payal Chandak, Shengchao Liu, Peter Van Katwyk, Andreea Deac, et al. 2023a. Scientific discovery in the age of artificial intelligence. *Nature* **620**(7972) 47–60.

Wang, Hanwen, Cheng Yi, Ting Li, Yue Yang, Tianyi Li. 2024a. The influence of AI-generated images on consumer behavior: Empirical evidence from an online real-estate platform .

Wang, Hongchang, Eric Overby. 2023. Do political differences inhibit market transactions? An investigation in the context of online lending. *Management Science* **69**(8) 4685–4706.

Wang, Hongchang, Yingjie Zhang, Tian Lu. 2025a. The power of disagreement: A field experiment to investigate human–algorithm collaboration in loan evaluations. *Management Science* .

Wang, Lingli, Ni Huang, Yumei He, De Liu, Xunhua Guo, Yan Sun, Guoqing Chen. 2025b. Artificial Intelligence (AI) assistant in online shopping: A randomized field experiment on a livestream selling platform. *Information Systems Research, Forthcoming* .

Wang, Lingli, Ni Huang, Yili Hong, Luning Liu, Xunhua Guo, Guoqing Chen. 2023b. Voice-based AI in call center customer service: A natural field experiment. *Production and Operations Management* **32**(4) 1002–1018.

Wang, Weiguang, Guodong Gao, Ritu Agarwal. 2024b. Friend or foe? Teaming between artificial intelligence and workers with variation in experience. *Management Science* **70**(9) 5753–5775.

Wang, Yiwei, Lauren Xiaoyuan Lu. 2024. Ship-Then-Shop as a promotional tool: Evidence from an online omnichannel fashion retailer. *Available at SSRN 4771684* .

Wiles, Emma, John J Horton. 2025. Generative AI and labor market matching efficiency. *Available at SSRN 5187344* .

Wu, Ji, Haichuan Zhao, Haipeng Chen. 2021. Coupons or free shipping? Effects of price promotion strategies on online review ratings. *Information Systems Research* **32**(2) 633–652.

Xie, Si, Siddhartha Sharma, Amit Mehra, Arslan Aziz. 2024. Strategic expectation setting of delivery time on marketplaces. *Information Systems Research* **35**(4) 1965–1980.

Xu, Yuqian, Hongyan Dai, Wanfeng Yan. 2024. Identity disclosure and anthropomorphism in voice chatbot design: A field experiment. *Management Science, Forthcoming* .

Zhang, Dennis J, Hengchen Dai, Lingxiu Dong, Fangfang Qi, Nannan Zhang, Xiaofei Liu, Zhongyi Liu, Jiang Yang. 2020. The long-term and spillover effects of price promotions on retailing platforms: Evidence from a large randomized experiment on Alibaba. *Management Science* **66**(6) 2589–2609.

Zheng, Zhanzhi, Shenyang Jiang, Yuqian Xu, Bradley R Staats. 2025. Video-based AI misconduct monitoring: Unintended consequences on operational outcomes. *Available at SSRN 5257644* .

Zhou, Eric, Dokyun Lee. 2024. Generative artificial intelligence, human creativity, and art. *PNAS Nexus* **3**(3) pgae052.

Appendix A: Figures and Tables

Figure A.1 Example of Collaborator Platform's Autonomous Delivery Vehicles Technology

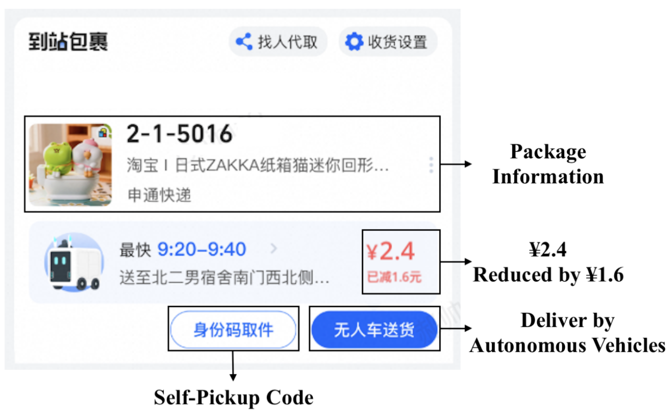

Figure A.2 Example of Redeeming a 40% off Coupon for Using Autonomous Delivery at Platform's App

Table A.1 Randomization Check for Single-Stage Treatment Subgroup and Control Group

	Autonomous Delivery Orders (Before March 1, 2023)	Proportion of iPhone Users	Station Autonomous Vehicle Count	Average Autonomous Delivery Price (RMB)	Prior-Year Station Package Volume
Groups	(1)	(2)	(3)	(4)	(5)
Single-Stage Strategy	0.000	0.265	2.942	2.423	1,049,971
Control Group	0.000	0.263	2.953	2.413	1,043,046
Difference	0.000	0.002	−0.011	0.010	6,925
t-Test p-value	—	0.6344	0.4818	0.2587	0.2261

Note. This table reports the means of key pre-treatment variables for the single-strategy treatment subgroup and the control group. Because the sample comprises first-time autonomous-delivery customers, prior orders are mechanically zero, yielding the result reported in Column (1). The unit of observation for the t-tests is the customer (N= 23,449).

Table A.2 Randomization Check for Multi-Stage Treatment Subgroup and Control Group

Groups	Autonomous Delivery Orders (Before March 1, 2023) (1)	Proportion of iPhone Users (2)	Station Autonomous Vehicle Count (3)	Average Autonomous Delivery Price (RMB) (4)	Prior-Year Station Package Volume (5)
Multi-Stage Strategy	0.000	0.261	2.942	2.400	1,035,185
Control group	0.000	0.262	2.952	2.413	1,043,046
Difference	0.000	-0.001	-0.010	-0.013	-7861
t-Test p-value	—	0.8919	0.6987	0.3061	0.3351

Note. This table reports the means of key pre-treatment variables for the multi-strategy treatment subgroup and the control group. Because the sample comprises first-time autonomous-delivery customers, prior orders are mechanically zero, yielding the result reported in Column (1). The unit of observation for the t-tests is the customer (*N*= 19,394).

Table A.3 Robustness Check on Effects of Price Promotions for Overall Sample

Panel A (≥ 5 $Packages$)	log(*Num. of Orders*)		log(*Num. of Full Price Orders*)	
Variables	*(1) Short (3.2-4.1)*	*(2) Long (4.2-5.1)*	*(3) Short (3.2-4.1)*	*(4) Long (4.2-5.1)*
$Treatment$	0.0160***	0.0013***	-0.0006^{***}	0.0013***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Observations	773,822	748,860	773,822	748,860
R-squared	0.0103	0.0014	0.0007	0.0013
Panel B (≥ 10 $Packages$)	log(*Num. of Orders*)		log(*Num. of Full Price Orders*)	
Variables	*(1) Short (3.2-4.1)*	*(2) Long (4.2-5.1)*	*(3) Short (3.2-4.1)*	*(4) Long (4.2-5.1)*
$Treatment$	0.0161***	0.0013***	-0.0005^{***}	0.0013***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Observations	727,818	704,340	727,818	704,340
R-squared	0.0104	0.0014	0.0006	0.0014
Panel C (≥ 15 $Packages$)	log(*Num. of Orders*)		log(*Num. of Full Price Orders*)	
Variables	*(1) Short (3.2-4.1)*	*(2) Long (4.2-5.1)*	*(3) Short (3.2-4.1)*	*(4) Long (4.2-5.1)*
$Treatment$	0.0161***	0.0013***	-0.0004^{***}	0.0013***
	(0.0003)	(0.0001)	(0.0000)	(0.0001)
Observations	684,418	788,280	684,418	788,280
R-squared	0.0103	0.0014	0.0005	0.0014
Date Fixed Effects	Yes	Yes	Yes	Yes
Station Fixed Effects	Yes	Yes	Yes	Yes

Note. Robust standard errors are given in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.4 Robustness Check on Effects of Price Promotions for Single-Stage Strategy

Panel A (≥ 5 $Packages$)	log(*Num. of Orders*)		log(*Num. of Full Price Orders*)	
Variables	*(1) Short (3.2-4.1)*	*(2) Long (4.2-5.1)*	*(3) Short (3.2-4.1)*	*(4) Long (4.2-5.1)*
$Treatment$	0.0071^{***}	-0.0001	-0.0010^{***}	-0.0001
	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Observations	687,704	665,520	687,704	665,520
R-squared	0.0042	0.0010	0.0011	0.0010
Panel B (≥ 10 $Packages$)	log(*Num. of Orders*)		log(*Num. of Full Price Orders*)	
Variables	*(1) Short (3.2-4.1)*	*(2) Long (4.2-5.1)*	*(3) Short (3.2-4.1)*	*(4) Long (4.2-5.1)*
$Treatment$	0.0070^{***}	-0.0001	-0.0010^{***}	-0.0001
	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Observations	643,622	622,860	643,622	622,860
R-squared	0.0042	0.0010	0.0009	0.0010
Panel C (≥ 15 $Packages$)	log(*Num. of Orders*)		log(*Num. of Full Price Orders*)	
Variables	*(1) Short (3.2-4.1)*	*(2) Long (4.2-5.1)*	*(3) Short (3.2-4.1)*	*(4) Long (4.2-5.1)*
$Treatment$	0.0068^{***}	-0.0001	-0.0010^{***}	-0.0001
	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Observations	602,144	582,720	602,144	582,720
R-squared	0.0041	0.0010	0.0008	0.0010
Date Fixed Effects	Yes	Yes	Yes	Yes
Station Fixed Effects	Yes	Yes	Yes	Yes

Note. Robust standard errors are given in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.5 Robustness Check on Effects of Price Promotions for Multi-Stage Strategy

Panel A (≥ 5 $Packages$)	log(*Num. of Orders*)		log(*Num. of Full Price Orders*)	
Variables	*(1) Short (3.2-4.1)*	*(2) Long (4.2-5.1)*	*(3) Short (3.2-4.1)*	*(4) Long (4.2-5.1)*
$Treatment$	0.0396^{***}	0.0049^{***}	0.0005^{***}	0.0048^{***}
	(0.0007)	(0.0003)	(0.0002)	(0.0003)
Observations	565,316	547,080	565,316	547,080
R-squared	0.0304	0.0027	0.0009	0.0026
Panel B (≥ 10 $Packages$)	log(*Num. of Orders*)		log(*Num. of Full Price Orders*)	
Variables	*(1) Short (3.2-4.1)*	*(2) Long (4.2-5.1)*	*(3) Short (3.2-4.1)*	*(4) Long (4.2-5.1)*
$Treatment$	0.0396^{***}	0.0048^{***}	0.0005^{***}	0.0048^{***}
	(0.0007)	(0.0003)	(0.0002)	(0.0003)
Observations	527,341	510,330	527,341	510,330
R-squared	0.0307	0.0027	0.0008	0.0027
Panel C (≥ 15 $Packages$)	log(*Num. of Orders*)		log(*Num. of Full Price Orders*)	
Variables	*(1) Short (3.2-4.1)*	*(2) Long (4.2-5.1)*	*(3) Short (3.2-4.1)*	*(4) Long (4.2-5.1)*
$Treatment$	0.0395^{***}	0.0048^{***}	0.0005^{***}	0.0047^{***}
	(0.0007)	(0.0003)	(0.0002)	(0.0003)
Observations	493,210	477,300	493,210	477,300
R-squared	0.0306	0.0028	0.0007	0.0028
Date Fixed Effects	Yes	Yes	Yes	Yes
Station Fixed Effects	Yes	Yes	Yes	Yes

Note. Robust standard errors are given in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.6 2SLS Analysis of Short-term Effects for New Customers

	(1)	(2)	(3)
Variables	*Redeemed Coupons*	$log($*Num. of Orders*$)$	$log($*Num. of Full Price Orders*$)$
$Treatment$	0.4444***		
	(0.0009)		
$\widehat{Redeemed\ Coupons}$		0.0361***	$-$0.0014***
		(0.0005)	(0.0001)
Date Fixed Effects	Yes	Yes	Yes
Station Fixed Effects	Yes	Yes	Yes
Observations	814,556	814,556	814,556

Note. Robust standard errors are given in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. The Cragg–Donald Wald F statistic for the first-stage analysis is 3.8×10^5, which exceeds the critical threshold suggested by Lee et al. (2022).

Table A.7 2SLS Analysis of Short-term Effects for Single-Stage Strategy

	(1)	(2)	(3)
Variables	*Redeemed Coupons*	$log($*Num. of Orders*$)$	$log($*Num. of Full Price Orders*$)$
$Treatment$	0.2771***		
	(0.0010)		
$\widehat{Redeemed\ Coupons}$		0.0257***	$-$0.0039***
		(0.0007)	(0.0002)
Date Fixed Effects	Yes	Yes	Yes
Station Fixed Effects	Yes	Yes	Yes
Observations	726,919	726,919	726,919

Note. Robust standard errors are given in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. The Cragg–Donald Wald F statistic for the first-stage analysis is 1.9×10^5, which exceeds the critical threshold suggested by Lee et al. (2022).

Table A.8 2SLS Analysis of Short-term Effects for Multi-Stage Strategy

	(1)	(2)	(3)
Variables	*Redeemed Coupons*	$log($*Num. of Orders*$)$	$log($*Num. of Full Price Orders*$)$
$Treatment$	0.8898***		
	(0.0011)		
$\widehat{Redeemed\ Coupons}$		0.0444***	0.0006***
		(0.0008)	(0.0002)
Date Fixed Effects	Yes	Yes	Yes
Station Fixed Effects	Yes	Yes	Yes
Observations	601,214	601,214	601,214

Note. Robust standard errors are given in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. The Cragg–Donald Wald F statistic for the first-stage analysis is 3.7×10^5, which exceeds the critical threshold suggested by Lee et al. (2022).

Table A.9 Robustness Check on Using Clustered Standard Errors

Panel A: Overall Sample	log(*Num. of Orders*)		log(*Num. of Full Price Orders*)	
Variables	*(1) Short (3.2-4.1)*	*(2) Long (4.2-5.1)*	*(3) Short (3.2-4.1)*	*(4) Long (4.2-5.1)*
$Treatment$	0.0160***	0.0013***	−0.0006***	0.0013***
	(0.0002)	(0.000=1)	(0.0001)	(0.0001)
Observations	814,556	788,280	814,556	788,280
R-squared	0.0103	0.0013	0.0007	0.0013

Panel B: Single-Stage	log(*Num. of Orders*)		log(*Num. of Full Price Orders*)	
Variables	*(1) Short (3.2-4.1)*	*(2) Long (4.2-5.1)*	*(3) Short (3.2-4.1)*	*(4) Long (4.2-5.1)*
$Treatment$	0.0071***	−0.0001	−0.0011***	−0.0001
	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Observations	726,919	703,470	726,919	703,470
R-squared	0.0041	0.0009	0.0011	0.0009

Panel C: Multi-Stage	log(*Num. of Orders*)		log(*Num. of Full Price Orders*)	
Variables	*(1) Short (3.2-4.1)*	*(2) Long (4.2-5.1)*	*(3) Short (3.2-4.1)*	*(4) Long (4.2-5.1)*
$Treatment$	0.0396***	0.0049***	0.0005***	0.0048 ***
	(0.0007)	(0.0003)	(0.0002)	(0.0003)
Observations	601,214	581,820	601,214	581,820
R-squared	0.0301	0.0025	0.0008	0.0025
Date Fixed Effects	Yes	Yes	Yes	Yes
Station Fixed Effects	Yes	Yes	Yes	Yes

Note. Standard errors clustered two-way by customer and date are given in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.10 Robustness Check on Using Raw Autonomous Delivery Order Count

Panel A: Overall Sample	*Num. of Orders*		*Num. of Full Price Orders*	
Variables	*(1) Short (3.2-4.1)*	*(2) Long (4.2-5.1)*	*(3) Short (3.2-4.1)*	*(4) Long (4.2-5.1)*
$Treatment$	0.0278^{***}	0.0022^{***}	-0.0010^{***}	0.0021^{***}
	(0.0005)	(0.0002)	(0.0001)	(0.0002)
Observations	814,556	788,280	814,556	788,280
R-squared	0.0086	0.0011	0.0006	0.0011

Panel B: Single-Stage	*Num. of Orders*		*Num. of Full Price Orders*	
Variables	*(1) Short (3.2-4.1)*	*(2) Long (4.2-5.1)*	*(3) Short (3.2-4.1)*	*(4) Long (4.2-5.1)*
$Treatment$	0.0119^{***}	-0.0023	-0.0017^{***}	-0.0025
	(0.0004)	(0.0020)	(0.0001)	(0.0020)
Observations	726,919	703,470	726,919	703,470
R-squared	0.0036	0.0008	0.0009	0.0008

Panel C: Multi-Stage	*Num. of Orders*		*Num. of Full Price Orders*	
Variables	*(1) Short (3.2-4.1)*	*(2) Long (4.2-5.1)*	*(3) Short (3.2-4.1)*	*(4) Long (4.2-5.1)*
$Treatment$	0.0698^{***}	0.0083^{***}	0.0009^{***}	0.0081^{***}
	(0.0013)	(0.0006)	(0.0003)	(0.0005)
Observations	601,214	581,820	601,214	581,820
R-squared	0.0251	0.0022	0.0007	0.0022
Date Fixed Effects	Yes	Yes	Yes	Yes
Station Fixed Effects	Yes	Yes	Yes	Yes

Note. Robust standard errors are given in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.11 Robustness Check on Using Alternative Dummy Dependent Variable

Panel A: Overall Sample	*Dummy of Autonomous Delivery Orders*		*Dummy of Full Price Autonomous Delivery Orders*	
Variables	*(1) Short (3.2-4.1)*	*(2) Long (4.2-5.1)*	*(3) Short (3.2-4.1)*	*(4) Long (4.2-5.1)*
$Treatment$	0.0184^{***}	0.0015^{***}	-0.0008^{***}	0.0015^{***}
	(0.0003)	(0.0002)	(0.0001)	(0.0002)
Observations	814,556	788,280	814,556	788,280
R-squared	0.0110	0.0014	0.0008	0.0013

Panel B: Single-Stage	*Dummy of Autonomous Delivery Orders*		*Dummy of Full Price Autonomous Delivery Orders*	
Variables	*(1) Short (3.2-4.1)*	*(2) Long (4.2-5.1)*	*(3) Short (3.2-4.1)*	*(4) Long (4.2-5.1)*
$Treatment$	0.0086^{***}	-0.0001	-0.0014^{***}	-0.0001
	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Observations	726,919	703,470	726,919	703,470
R-squared	0.0043	0.0010	0.0012	0.0010

Panel C: Multi-Stage	*Dummy of Autonomous Delivery Orders*		*Dummy of Full Price Autonomous Delivery Orders*	
Variables	*(1) Short (3.2-4.1)*	*(2) Long (4.2-5.1)*	*(3) Short (3.2-4.1)*	*(4) Long (4.2-5.1)*
$Treatment$	0.0443^{***}	0.0057^{***}	0.0006^{***}	0.0057^{***}
	(0.0007)	(0.0004)	(0.0002)	(0.0004)
Observations	601,214	581,820	601,214	581,820
R-squared	0.0321	0.0026	0.0009	0.0025
Date Fixed Effects	Yes	Yes	Yes	Yes
Station Fixed Effects	Yes	Yes	Yes	Yes

Note. Robust standard errors are given in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.12 Robustness Check on Using Alternative Percentage Dependent Variable

Panel A: Overall Sample	*Percentage of Autonomous Delivery Orders*		*Percentage of Full Price Autonomous Delivery Orders*	
Variables	*(1) Short (3.2-4.1)*	*(2) Long (4.2-5.1)*	*(3) Short (3.2-4.1)*	*(4) Long (4.2-5.1)*
$Treatment$	0.0135***	0.0011***	-0.0006^{***}	0.0011***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Observations	814,556	788,280	814,556	788,280
R-squared	0.0100	0.0013	0.0007	0.0013
Panel B: Single-Stage	*Percentage of Autonomous Delivery Orders*		*Percentage of Full Price Autonomous Delivery Orders*	
Variables	*(1) Short (3.2-4.1)*	*(2) Long (4.2-5.1)*	*(3) Short (3.2-4.1)*	*(4) Long (4.2-5.1)*
$Treatment$	0.0036***	-0.0001	-0.0007^{***}	-0.0001
	(0.0001)	(0.0003)	(0.0000)	(0.0003)
Observations	726,919	703,470	726,919	703,470
R-squared	0.0026	0.0006	0.0008	0.0006
Panel C: Multi-Stage	*Percentage of Autonomous Delivery Orders*		*Percentage of Full Price Autonomous Delivery Orders*	
Variables	*(1) Short (3.2-4.1)*	*(2) Long (4.2-5.1)*	*(3) Short (3.2-4.1)*	*(4) Long (4.2-5.1)*
$Treatment$	0.0328***	0.0044***	0.0003**	0.0043***
	(0.0006)	(0.0003)	(0.0001)	(0.0003)
Observations	601,214	581,820	601,214	581,820
R-squared	0.0292	0.0025	0.0008	0.0024
Date Fixed Effects	Yes	Yes	Yes	Yes
Station Fixed Effects	Yes	Yes	Yes	Yes

Note. Robust standard errors are given in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.13 Robustness Check on Excluding April 2 for Long-Term Analysis

	$log(\textit{Num. of Full Price Orders})(4.3-5.1)$		
Variables	$(1)\ Overall\ Sample$	$(2)\ Single\ Stage$	$(3)\ Multi\ Stage$
$Treatment$	0.0013***	-0.0001	0.0046***
	(0.0006)	(0.0002)	(0.0003)
Date Fixed Effects	Yes	Yes	Yes
Station Fixed Effects	Yes	Yes	Yes
Observations	762,004	608,021	564,543
R-squared	0.0013	0.0009	0.0024

Note. Robust standard errors are given in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.14 Survival Analysis of Long-Term Adoption

	First Autonomous Delivery Order			*First Full Price Autonomous Delivery Order*		
Variables	$Overall\ Sample$	$Single\_Stage$	$Multi\_Stage$	$Overall\ Sample$	$Single\_Stage$	$Multi\_Stage$
$Treatment$	1.5078***	1.0883	2.4759***	1.4973***	1.0822	2.4506***
	(0.0718)	(0.0621)	(0.1552)	(0.0716)	(0.0620)	(0.1544)
Station Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26,276	23,449	19,394	26,276	23,449	19,394

Note. Robust standard errors are given in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.15 Short-term Spillover Effects Excluding Customers Without Packages After Coupon

	log(*Num. of Orders*)		log(*Num. of Full Price Orders*)	
Variables	(1) $Overall\ Sample$	(2) $Single\_Stage$	(3) $Overall\ Sample$	(4) $Single\_Stage$
$Treatment$	0.0152***	0.0048***	−0.0006***	−0.0011***
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Date Fixed Effects	Yes	Yes	Yes	Yes
Station Fixed Effects	Yes	Yes	Yes	Yes
Observations	790,903	703,266	790,903	703,266
R-squared	0.0100	0.0026	0.0007	0.0011

Note. Robust standard errors are given in parentheses. $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.16 Short-term Spillover Effects with Alternative Percentage Dependent Variable Excluding Dates Using Coupons

	Percentage of Full Price Autonomous Delivery Orders	
Variables	(1) $Overall\ Sample$	(2) $Single\_Stage$
$Treatment$	−0.0006***	−0.0007***
	(0.0001)	(0.0000)
Date Fixed Effects	Yes	Yes
Station Fixed Effects	Yes	Yes
Observations	808,586	724,799
R-squared	0.0007	0.0008

Note. Robust standard errors are given in parentheses. $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.17 Robustness Check on Using Weekly-Aggregated Data

Panel A: Overall Sample	log(*Num. of Orders*)		log(*Num. of Full Price Orders*)	
Variables	*(1) Short (3.2-4.1)*	*(2) Long (4.2-5.1)*	*(3) Short (3.2-4.1)*	*(4) Long (4.2-5.1)*
$Treatment$	0.1723***	0.0130***	−0.0059***	0.0128***
	(0.0030)	(0.0015)	(0.0008)	(0.0015)
Observations	131,380	131,380	131,380	131,380
R-squared	0.0500	0.0066	0.0031	0.0065
Panel B: Single-Stage	log(*Num. of Orders*)		log(*Num. of Full Price Orders*)	
Variables	*(1) Short (3.2-4.1)*	*(2) Long (4.2-5.1)*	*(3) Short (3.2-4.1)*	*(4) Long (4.2-5.1)*
$Treatment$	0.0739***	−0.0014	−0.0106***	−0.0015
	(0.0022)	(0.0013)	(0.0006)	(0.0013)
Observations	117,245	117,245	117,245	117,245
R-squared	0.0219	0.0049	0.0045	0.0049
Panel C: Multi-Stage	log(*Num. of Orders*)		log(*Num. of Full Price Orders*)	
Variables	*(1) Short (3.2-4.1)*	*(2) Long (4.2-5.1)*	*(3) Short (3.2-4.1)*	*(4) Long (4.2-5.1)*
$Treatment$	0.4328***	0.0495***	0.0054***	0.0489***
	(0.0084)	(0.0038)	(0.0018)	(0.0038)
Observations	96,970	96,970	96,970	96,970
R-squared	0.1346	0.0116	0.0037	0.0114
Week Fixed Effects	Yes	Yes	Yes	Yes
Station Fixed Effects	Yes	Yes	Yes	Yes

Note. Robust standard errors are given in parentheses. $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.