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Abstract

This study conducts a randomized field experiment to examine the presence of the attraction effect in real-world purchasing situations. While previous research has confirmed the existence of the attraction effect in controlled environments, it has not been extensively tested in actual purchasing scenarios where consumers tend to think more analytically and the products are not represented numerically scenarios. In real-life situations, consumers use their own resources, which can affect their decision-making processes. Especially, the attraction effect is shown to be often driven by System 1, which involves intuitive and quick decision-making. This study tests the effect in an online subscription service where consumers may rely more on System 2, where the creators were randomly encouraged to create a decoy option. The results show that the attraction effect exists in real-world contexts, with the addition of a decoy plan significantly boosting sales.

Keywords: attraction effect, randomized field experiment

1. Introduction

Contrary to rational choice theory, which assumes that the utility of alternatives is independent of context and that the preference order between two alternatives remains unchanged across different contexts, various experimental studies have shown that consumer choices are often context dependent. One of the most well-known and widely reported of the "context effects" is the attraction effect. In the case of the attraction effect, introducing the "third" option (called the decoy) that is clearly inferior to another option in the set increases the probability that this superior option (called the target) will be chosen over the remaining option (called the competitor). Even though the original options do not dominate one another, adding the decoy makes the target option seem more appealing compared to the competitor.

This phenomenon has been extensively tested in many experimental studies due to its numerous implications for marketing, and it has been demonstrated that the effect indeed exists. Huber et al. (1982) is a highly influential experimental study that first demonstrated the existence of the attraction effect. The study challenged traditional rational choice theory, which assumes that consumers' preferences are stable and that adding options should not change the ranking of existing choices. Following Huber et al.'s work, many studies replicated and expanded on their findings, confirming the robustness of the attraction effect across different product categories and decision contexts.

However, the attraction effect in consumer choice problems has mainly been tested in controlled laboratory experiments and has not been sufficiently examined in real-world situations involving actual purchases. Frederick et al. (2014) questioned the practical relevance of this effect, arguing that the effect is often contingent on highly specific conditions, namely, abstract and numerical scenarios. They state “The authors posit that perceptual representations of attributes do not support the sorts of comparisons that drive the attraction effect with highly stylized examples, and they question the practical significance of the effect” (p. 487). In general, laboratory experiments take place in controlled environments, which often differ from real-world purchasing situations. In real life, consumer decisions are influenced by various complex factors such as time constraints, social influences, past experiences, and emotional states. These factors are often excluded in laboratory settings, meaning that the results from experiments may not fully apply to actual consumer behavior.

In addition, lab experiments participants often make choices without spending their own money, unlike in real-world purchasing decisions. In real-life situations, consumers use their own resources, which can affect their decision-making processes. Especially, the attraction effect is shown to be often driven by System 1, which involves intuitive and quick decision-making (Pocheptsova et al. 2009; Mao and Oppewal, 2012; Crosetto and Gaudeul, 2024). However, in real-world situations involving actual purchases, consumers may rely more on System 2, which is deliberate and analytical (Pherson et al., 2024). In perceptual decisions, the principle of loss aversion does not apply because there is no potential for loss, resulting that only the first stage of the integrated dual-system framework is relevant for predicting preference construction, while the second stage does not play a role (Padamwar and Dawra, 2024). Hence, to accurately test the attraction effect in consumer choice problems, we need to examine how it operates in real-world scenarios where System 2 is more likely to be engaged. This deeper cognitive engagement may reduce the influence of System 1-driven biases like the attraction effect.

In this article, in addition to real-world observational studies, we conduct randomized field experiments to examine the existence of attraction effect, in which consumers face more concrete and less stylized stimuli, and they invest their own money, making them more motivated to carefully consider their choices. To our knowledge, this is the first randomized field experiment which examined the existence of the attraction effect. In the randomized field experiments, we used real-world data from an online subscription service where creators sell their work through subscription models. The experiment involved introducing a decoy option to see if it would increase the likelihood of choosing a target option. Specifically, creators were encouraged to create a decoy option, and we examined whether this intervention improved the selection rate of the target subscription option. We also investigated the heterogeneity of the attraction effect. Some research has examined the heterogeneity among consumers in relation to the attraction effect, indicating that different cognitive processing styles play a role. We also examined such heterogeneities using our real-world data.

Section 2 surveys relevant theoretical and empirical research on the attraction effect. In Section 3, before conducting randomized field experiments, analysis based on an observational study in the same service is presented. Section 4 executes the randomized field experiments and the results. Section 5 discusses the implications and limitations.

2. Related literature

2.1. The nature of Attraction effect

The attraction effect is a phenomenon in decision-making where introducing an inferior or decoy option into a set of choices makes a target option more appealing in comparison to other alternatives. The decoy is asymmetrically dominated, meaning it is worse than the target in at least one key attribute, while being comparable to or better than another option. This shifts the consumer's preference toward the target, even though the decoy is not expected to be chosen. The attraction effect has been widely studied with research highlighting its impact on consumer decision-making. This is because it sheds light on how context and choice architecture influence consumer decisions, challenging the traditional assumption that consumers make purely rational choices. Moreover, this effect became an important tool in marketing, as introducing decoys could be used strategically to nudge consumers toward a preferred option.

Several research has explained why the effect occurs. Simonson (1989) argued that the attraction effect is partly due to consumers' desire to justify their choices. That is, when a decoy is present, the superior features of the target become more obvious, making it easier for consumers to justify their choice. Another explanation is shifting of attribute weights (Ariely and Wallsten 1995). They argue that the presence of a decoy changes the way consumers value different product attributes. When a decoy is introduced, consumers tend to increase the importance of the attributes where the target option outperforms the decoy, making the target more attractive. A loss aversion can also explain the effect. When a decoy option is introduced, the target option seems like a gain compared to the decoy, while the competitor might be perceived as riskier (Pettibone and Wedell 2000). This drives consumers to choose the target to minimize the potential loss they associate with the competitor, even though that loss is only perceived.

A lot of experimental studies investigated the conditions under which the attraction effect is more or less likely to occur. For example, the effect is particularly strong in scenarios where consumer faces a higher level of construal (Khan et al. 2011), choices between durable product category (Milberg et al. 2014; Neumann et al. 2016) or utilitarian product category (Neumann et al. 2016). A review summarizing the situations in which the attraction effect is more likely or less likely to occur is presented in Padamwar and Dawra (2024).

2.2. Replication in laboratory experiments

The effect has been replicated in laboratory experiments. Huber et al. (1982) is the first to demonstrate the existence of the attraction effect. They showed that introducing a decoy option that is clearly dominated by the target option increases the likelihood that the target will be chosen. Huber and Puto (1983), Simonson (1989), Simonson and Tversky (1992), and Park and Kim (2005) also showed that the attraction effect is observed in several situations.

The existence of the effect is also examined in the neuroscience field. Using functional MRI (fMRI), Hedgcock and Rao (2009) investigated the neural basis of the attraction effect. It demonstrated how brain regions are activated when consumers face trade-offs and decoy options, showing that a decrease in brain activity associated with negative emotions and suggested that trade-off aversion is a key driver of the attraction effect. This research added a neuropsychological perspective to the study of the attraction effect. Hu and Yu (2014) also demonstrated that the decoy effect is not just a cognitive phenomenon but also has identifiable neural underpinnings using fMRI, showing that how and why people are influenced by irrelevant options in their decision-making processes.

However, several research doubt the practical effectiveness of the attraction effect. For example, Frederick et al. (2014) examined the robustness of the attraction effect and questioned the practical relevance of this phenomenon. They found that the attraction effect is often contingent on highly specific conditions, such as abstract or stylized stimuli (e.g., numerical comparisons), rather than real-world, naturalistic settings (e.g., pictorial stimuli). More Specifically, they found the attraction effect in 4 out of 5 cases where the choice set attributes were numerically represented, however, in experiments involving perceptual representations (e.g., pictures of fruit), verbal descriptions (e.g., quality explained in text), or direct experience (e.g., tasting a drink), they only found the effect in 2 instances. Some experiments even showed a decrease in the target option's selection rate when a decoy was introduced.

Another research raises doubts about how frequently the attraction effect occurs in everyday decision-making and suggests that it may not be as universal as previously believed. Yang and Lynn (2014) replicated Frederick et al. (2014)'s experiment by conducting 91 choice scenarios. Of these, 37 scenarios used only numerical representations of attributes, 12 included images, and 42 involved verbal descriptions. They found significant attraction effects in only 12% of scenarios, with 24% of scenarios using numerical representations, and only 4% of scenarios involving qualitative or image-based attributes. These results support Frederick et al.'s findings, indicating the attraction effect is more likely in abstract, numerical scenarios.

2.3. Thoughtful, deliberate thinking and the attraction effect

As explained in the previous section, the attraction effect has been demonstrated in specific laboratory settings, but their reproducibility in real-world purchasing situations and their ability to explain actual purchase decisions remain questionable.[…] There are numerous studies examining the conditions under which the attraction effect occurs in consumers, with many specifically discussing the relationship between thoughtful, deliberate, and analytical thinking and the attraction effect.

Masicampo and Baumeister (2008) found that participants of their experiment who consumed sugar, which elevated their blood glucose levels, were better able to engage in effortful processing, resulting in a decrease in the attraction effect. Pocheptsova et al. (2009) investigated the attraction effect in the context of cognitive resource depletion using tasks like the Stroop test. Their research demonstrated that when participants' cognitive resources were depleted (i.e., after performing a Stroop task), the attraction effect became more pronounced.

Several studies have examined the relationship between dual process perspective (e.g., Epstein et al. 1996; Kahneman and Frederick 2005) and the attraction effect. Mao and Oppewal (2012) explored the relationship between rational–experiential inventory (REI) (Epstein et al.1996; Pacini and Epstein 1999) and the attraction effect in relation to the dual process theory. They found that consumers who rely on intuitive decision-making (System 1) are more susceptible to the attraction effect. Dhar and Gorlin (2013) discussed the role of System 1 in decision-making biases like the attraction effect. They argue that this effect operates through the intuitive, automatic nature of System 1, as consumers quickly judge one option to be better in comparison to a decoy without engaging in deeper, analytical thinking.

In summary, the level of deliberation plays a significant role in moderating the attraction effect. Quick, heuristic-based decisions lead to a stronger effect, while deeper reflection and analysis help consumers avoid being influenced by irrelevant decoy options.

3. Observational study

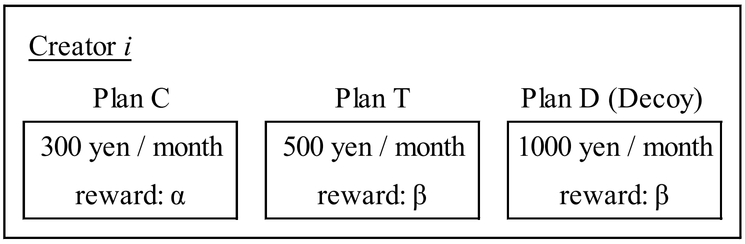
3.1. The platform

In this study, we use data from pixivFANBOX, a fan community service, to examine the presence of the attraction effect in real-world settings. First, we provide an overview of the service and its characteristics. pixiv is an illustration communication platform operated by pixiv Inc., widely popular in Japan as a space for creators to engage in creative activities and interact with fans. As of December 2023, pixiv had approximately 93 million users, with around 1.2 billion works posted. We execute a randomized field experiment on this platform.

In this service, creators can create monthly plans to solicit support, setting the content, number of rewards, and pricing as they see fit. Users (*i.e.* subscribers) can purchase these plans to support creators' activities, with the support being provided on a monthly basis and the option to cancel at any time. One notable feature of this service is that the creators can offer decoy plans at their own discretion. Because creators have control over the pricing and rewards, many who offer multiple plans create decoy options—plans that are more expensive but offer no additional benefits compared to other plans. This allows for the creation of decoy options, which serve as a practical illustration of the attraction effect.

Figure 1 illustrates an example of a creator plan. The user might find it difficult to choose between Plan C and Plan T, as they represent a trade-off between price and reward. With the introduction of Plan D (Decoy), the situation changes. Plan D is priced at the highest, but it only offers the same reward as Plan T. Hence, Plan D is clearly a worse plan than Plan T.

Figure 1 Example of a plan



3.2. An overview of the observational study

Before introducing randomized field experiments, we analyze the impact of adding decoy plans on creators' sales and the factors behind it from both the creators' and users' perspectives using observational data in this section. First, we explain the two types of data used in this study, then clarify the assumptions and potential biases in the actual data.

The first data used for this observational study is derived from monthly sales data of creators in two periods: May 2021 and August 2021. The addition of decoy plans between June and July 2021 is defined as the treatment. The sample includes creators who, as of May 2021, held two regular plans and had no changes in the number of plans aside from the treatment. Creators who added a decoy plan during this period were classified as the treatment group, while those who did not were classified as the control group. Then, we confirm if the addition of the decoy plan increases the sales of the creators, and simultaneously changes the choice of the users.

The second data consists of cross-sectional data observed at two points in time: October 2022 (t1) and January 2023 (t2). The creators included are those who, at t1, offered two regular plans; competitor plan (C) and target plan (T) and, at t2, either continued to offer the same two regular plans or added a decoy plan (D) to form a set of three options (C, T, and D). We examine how the presence of a decoy plan affects the probability of selecting the target plan (T), while controlling for user attributes and purchasing behaviors.

3.3. Model 1a: the creator analysis

In Model 1a, we examine the data observed from the creators' perspective using the Difference-in-Differences (DID) estimation method. DID is a statistical technique used in econometrics and social sciences to estimate the causal effect of a treatment or intervention. It is particularly useful when randomized control trials are not feasible. DID compares the differences in outcomes between a treatment group and a control group before and after the intervention.

Let $d \in \{0,1\}$ be the binary treatment value, where $d = 1$ if a creator creates a decoy plan, and $d = 0$ if not. We also denote pre-treatment as $p = 0$, and post-treatment as

$p = 1$. The outcome variable is denoted as y. A primitive method would be to take the difference in outcomes between the two groups after the treatment:

$$E(y|d = 1, p = 1) - E(y|d = 0, p = 1).$$

However, the treatment group and control group may differ qualitatively. Simple average differences might not account for other external factors that change over time and affect both the treatment and control groups. DID adjusts for such time-varying factors by looking at the change in outcomes, not just the levels, between pre- and post-intervention periods for both groups. The DID estimator is defined as[1]:

$$\{E(y|d = 1, p = 1) - E(y|d = 1, p = 0)\} - \{E(y|d = 0, p = 1) - E(y|d = 0, p = 0)\}.$$

By introducing subscript i for each creator and t for time, the DID regression is represented as follows:

$$y_{it} = \alpha + \beta d_i + \gamma p_t + \delta(d_i \times p_t) + \epsilon_{i,t}$$

where ϵ denotes the error term. The estimated coefficient δ corresponds to the DID estimator.The dependent variable y is the logarithms of sales: *log(Sales)*, supporters: *log(Supporters)*, and unit price *log(UnitSales)*.

3.4. Model 1b: the user analysis

While Model 1a focused on the creators' perspective, Model 1b uses user data and

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[1] DID assumes that, in the absence of treatment, the treatment and control groups would have experienced similar trends over time. By comparing changes in outcomes over time between the two groups, DID removes biases that arise from pre-existing differences between the groups.

performs logistic regression analysis to examine how the likelihood of selecting each plan changes based on user attributes. In Model 1b, we use logistic regression analysis, employing cross-sectional data observed at two points in time (*i.e.* t1: October 2022, and t2: January 2023). In particular, we focus on users who are making a new purchase from the creators' plans and examine whether the inclusion of a decoy plan D influences the likelihood of choosing the target plan T. The dependent variable for this analysis is the likelihood of a user selecting the T, as opposed to the competitor plan C.

Additionally, in the two groups where the choice sets are (C, T) and (C, T, D), both groups had only the (C, T) option at t1, and it is only at t2 that the distinction between (C, T) and (C, T, D) emerged. Therefore, t1 can be considered as before the treatment by the creators, and t2 as after the treatment. Specifically, users who were presented with a choice set that included D and users who were presented with a set that did not include D are classified using the $Decoy_i$ (plan choice dummy), and the probability of selecting T is examined for each user attribute.

This binary choice is modeled using a logistic regression, which estimates the probability of choosing the target plan given the presence or absence of a decoy plan as follows;

$$logit\ \Pr(y_i = 1) = \alpha + \beta_1 Decoy_i + \beta_2 Purchase_i + \beta_3 Decoy_i \times Purchase_i$$

where $Decoy_i$ denotes dummy variable representing whether the decoy plan D is included in the choice set (1 if present, 0 if not), $Purchase_i$ denotes the number of creators a user has purchased from within a month. $Purchase_i$ is included to control for the heterogeneity of the uses. This allows us to examine how the probability of selecting T is affected as a user purchases from more creators' options simultaneously.

The sample size was determined by randomly selecting 5,000 users each from the groups where the choice sets were (C, T) and (C, T, D), resulting in a total sample size of n = 10,000.

3.5. Results for model 1a

The results of the DID regression are shown in Table 1. The dependent variables are the logarithms of sales, supporters, and unit price. Sales were positively significant at the 1% level, with an increase rate of 0.6% by adding the decoy plan. The results also suggest a weak tendency for unit prices to increase, supporting that the addition of decoy plans positively affects creators' sales.

Table 1 Results for model 1a

y	0-100%	0-25%	25-75%	75-100%
log(sales)	0.634**	0.951***	0.574***	0.401***
log(Supporters)	0.370	0.538***	0.325	0.239
log(UnitSales)	0.264***	0.413**	0.249*	0.161

3.6. Results for model 1b

The results of the logistic regression analysis at the two time points are shown in Table 2. Focusing on the time t1, the coefficient for Decoy is not significant relative to the reference category CT (Decoy = 0) with odds ratio 0.934. This is consistent with the fact that at time t1, before the addition of the decoy plan, there is no difference in the content of the choice sets between (C, T) and (C, T, D). On the other hand, at time t2, the coefficient for Decoy becomes positively significant with odds ratio 1.714, indicating that T is more likely to be selected in (C, T, D) compared to (C, T).

These results suggest that, at the point when the creators who would later add D only had (C, T), there was no significant difference in the likelihood of T being selected compared to creators who would continue to offer only (C, T) without adding D in the future. However, when D was added and users were presented with the (C, T, D) choice set, the proportion of users selecting T increased (with the difference test showing 1% significance). Therefore, the presence of D has a positive effect on the relative selection rate of T among (C, T).

Table 2 Results for model 1b

	t1			t2		
	Estimate	Odds	P-value	Estimate	Odds	P-value
Intercept	0.120	1.127	0.010**	0.062	1.064	0.170
Decoy	-0.068	0.934	0.696	0.539	1.714	0.003***
Purchase	-0.081	0.922	0.004***	-0.070	0.933	0.012**
Decoy×*Purchase*	-0.076	0.927	0.646	-0.379	0.684	0.026**

4. Randomized field experiment

4.1. An overview of the randomized field experiment

In the observational study, an analysis was conducted to draw conclusions regarding the existence of the attraction effect; however, certain concerns remain. To strengthen the conclusions, a randomized field experiment was conducted with actual creators on the platform, based on the findings obtained from the observational study.

It is widely known that randomized controlled trials (RCTs) are considered the most robust experimental method for evaluating causal effects. However, due to ethical and cost-related constraints, the feasibility of conducting RCTs in real-world settings is very limited. For example, noncompliance is common, where some participants assigned to the intervention group do not actually receive or execute the intervention. In such cases, when conducting RCTs is difficult, an effective experimental method incorporating randomization is the randomized encouragement design (RED).

The experiment was conducted between November 2022 and January 2023 using pixiv platform. As part of the intervention, emails were sent to creators on November 10, 2022, and December 5, 2022, encouraging them to add a decoy plan. The creators targeted for the experiment were those who, as of November 9, 2022, had two regular plans but did not have a decoy plan. A total of 8,578 eligible creators were randomly assigned to either the intervention group (7,584 creators), who received the email, or the control group (994 creators), who did not receive the email. For the analysis, 4,210 cases that did not generate sales before or after the intervention were excluded, resulting in a final sample size of 3,952 creators (3,485 in the intervention group and 467 in the control group).

In this study, even if an email is used as an intervention to encourage the addition of a decoy plan, not all creators in the intervention group will necessarily add the decoy plan, and it is also possible that creators in the non-intervention group may still add decoy plans. The execution rates are 0.044 for the intervention group (who created a decoy plan after they receive encouragement e-mail), and 0.009 for the control group (who created a decoy plan even though they did not receive the e-mail).

4.3. Model 2a: the creator analysis

Let $z \in \{0,1\}$ be the binary instrumental variable, and $d \in \{0,1\}$ be the binary actual treatment value. Specifically, $z = 1$ if a creator is assigned to the intervention group (encouraged to create a decoy plan), and $z = 0$ if a creator is assigned to the non-intervention group. In addition, $d = 1$ if a creator actually creates a decoy plan, and $d = 0$ if not.

The assignment observed under $z = 1$ is denoted as d_1, and under $z = 0$, it is denoted as d_0. Similarly, the outcome variable is y_1 if $d = 1$ and y_0 if $d = 0$. Thus, we have following equations:

$$d = zd_1 + (1 - z)d_0$$

$$y = dy_1 + (1 - d)y_0$$

In this experiment, Compliers are creators who add decoy plans upon receiving the email and do not add decoy plans if they do not receive the email. Other groups include Always-takers (who add decoy plans regardless of receiving the email), Never-takers (who do not add decoy plans regardless of receiving the email), and Defiers (who add decoy plans when they do not receive the email but do not add them when they do receive the email).

In this scenario, assuming Defiers do not exist and that $d_1 \geq d_0$ (monotonicity assumption), Imbens and Angrist (1994) defined the local average treatment effect (LATE) as:

$$LATE = E(y_1 - y_0 | d_1 = 1, d_0 = 0)$$

As the name suggests, this represents the local average treatment effect, not the overall average treatment effect, but rather the average treatment effect for Compliers (Angrist et al., 1996). LATE is estimated using two-stage least squares (2SLS).

As an outcome y, we consider monthly creator's gain indicators after the intervention; January 2023. We include the natural logarithm of sales, number of supporters, and the average unit sales per supporter, denoted as *log(Sales)*, *log(Supporters)*, and *log(UnitSales)*, respectively.

We estimate the LATE using two stage least squares (2SLS). In the first stage regression, we employ

$$d_i = \gamma + \delta z_i + u_i,$$

and in the second stage, we employ

$$y_i = \alpha + \beta \hat{d}_i + \epsilon_i,$$

where $\hat{d}_i$ is the predicted value of the first stage d_i.

4.4. Model 2b: the user analysis

Based on the findings from the intervention experiment, which showed that adding a decoy plan increases creators' sales, Model 2b examines whether the increase in sales can be attributed to the attraction effect as an indirect influence of the decoy plan. Specifically, it focuses on customer unit price changes based on the selection ratio between plans and examines whether the addition of a decoy plan influenced the selection ratio of the target option. In Model 1b, a logistic regression analysis was conducted using cross-sectional data from the users' side, suggesting that the decoy plan may have a positive impact on the selection ratio of the target plan. Building on this, the goal of this analysis is to obtain more robust results using the intervention experiment data, where the homogeneity between the intervention and control groups is ensured by random assignment.

The dataset used for this intervention experiment is similar to the one described in Section 4.3, with two key differences: the addition of user attributes and changes in the dependent variable used for analysis. Like in Section Model 1b, the observed users are limited to new customers, as it is expected that the attraction effect will be more appropriately tested in situations where the users are sufficiently aware of their options (Simonson, 2014). The unit price of the common (C, T) (standard plans) portion among all creators was observed at two points in time: t1 (October 2022) and t2 (January 2023). From the creators' perspective, there is no need to differentiate between the revenue generated by the high-priced target plan T and the even higher-priced decoy plan D among the regular plans. However, to obtain more robust results, we follow the analysis approach of Weinmann et al. (2022) and focus solely on observing the CT portion.

For analysis, the dependent variable is y, representing the logarithmic increase rate of the customer unit price for (C, T) at times t1 and t2. This is expressed as the difference between log(UnitSales) before and after the intervention;

$$y = \log(Customer\ UnitSales\ CT_{t2}) - \log\,(Customer\ UnitSales\ CT_{t1})$$

If the principle of independence (Luce, 1977) holds in real-world data, there should be no significant changes in y caused by the addition of new options. This would imply that the introduction of decoy options does not affect the relative selection ratio of the existing (C, T) plans. But if the attraction effect exists, the proportion of upgrades from T to D is generally higher than from C to D. Therefore, it is expected that, with the addition of D, the likelihood of users who would have originally chosen T now choosing D is higher than the likelihood of users who would have chosen C switching to T. Consequently, if y is affected by the addition of D, it is generally expected to fluctuate in a negative direction.

4.5. Results for model 2a

Table 4 presents the LATE estimated using 2SLS for each outcome. In the analysis, the creators were divided into four quartiles based on their sales volume before the intervention. The results showed that the increase in sales was not significant in quartiles (a), (b), and (d), but was significantly positive in quartile (c). In this quartile, it was found that adding a decoy plan increased the creator's sales by approximately 5.7%, which is more prominent than that of observational study. Additionally, the increase in sales was associated with an increase in the number of supporters, as opposed to an increase in unit price.

Table 3 Results for model 2a

	y	Estimate	Std. Error	P-value
(a) 0-100%	*log(Sales)*	5.430*	2.820	0.054
	log(Supporters)	6.043**	2.578	0.019
	log(UnitSales)	-0.613	0.924	0.507
(b) 0-25%	*log(Sales)*	-2.271	3.294	0.491
	log(Supporters)	-0.208	2.645	0.937
	log(UnitSales)	-2.064	2.513	0.412
(c) 25-75%	*log(Sales)*	5.750***	2.044	0.005
	log(Supporters)	6.302***	2.247	0.005
	log(UnitSales)	-0.552	1.244	0.657
(d) 75-100%	*log(Sales)*	0.084	2.174	0.969
	log(Supporters)	1.615	2.406	0.502
	log(UnitSales)	1.531	1.162	0.188

4.6. Results for model 2b

Table 4 shows the results of the instrumental variable estimates obtained using the two-stage least squares method. As a result, it was found that the logarithmic growth rate of customer unit prices before and after the intervention was positively significant in quantile (c). This suggests that the addition of the decoy plan caused a behavioral change in users when selecting the existing CT plans.

Table 4 Results for model 2b

	y	Estimate	Std. Error	P-value
(a) 0-100%	*Intercept*	-0.015	0.030	0.661
	β	0.447	0.447	0.317
(b) 0-25%	*Intercept*	-0.134	0.130	0.307
	β	3.120	2.308	0.178
(c) 25-75%	*Intercept*	-0.095*	0.049	0.050
	β	1.347**	0.682	0.049
(d) 75-100%	*Intercept*	8.181**	0.111	0.550
	β	2.368	3.350	0.481

5. Concluding remarks

5.1. Academic and managerial implications

In this study, we analyzed the impact of adding decoy plans on creators' sales and the factors behind it using randomized field experiments. We confirmed that adding decoy plans increased the monthly average sales of creators. Moreover, in the intervention experiment, it was found that creators who added decoy plans could expect an additional 5.7% in rewards compared to those who did not. In this section, we discuss the academic contributions and managerial implications derived from these results. We also address the limitations of this research and prospects for future studies.

The following can be considered as academic contributions. This study significantly advances the understanding of the attraction effect by demonstrating its applicability in a real-world marketplace, specifically within a randomized field experiment framework. While prior research on the attraction effect has been primarily limited to laboratory settings, this study breaks new ground by examining how decoy options influence consumer behavior in an actual commercial context, thereby providing more external validity to existing theories.

Second, we examined the heterogeneity of the attraction effect. Testing consumer and product heterogeneity related to the attraction effect using real-world data provides valuable insights that enhance the applicability of academic findings. We showed that, as is suggested in the prior experimental investigations, the effectiveness of the effect is very variable depending on the consumer or product characteristics in the field data.

Furthermore, the following points can be highlighted as practical contributions. First, this study demonstrates that adding a decoy plan can effectively boost sales with minimal additional effort on the part of the creator. Since the decoy plan is designed to be inferior in comparison to the main options, its addition requires little to no extra content creation or value addition. This provides sellers with a low-effort, high-reward strategy to increase their revenue, making it a practical recommendation for creators seeking to optimize their product offerings. While the study is conducted within a fan community platform, the implications extend to other digital marketplaces and subscription models. The strategic use of decoy options to influence consumer choices can be applied across industries, such as streaming services, software subscriptions, or e-commerce platforms where multiple product tiers are offered. This makes the research findings applicable to a wide range of businesses that rely on tiered pricing or bundled services to increase revenue.

We also highlight how subtle behavioral nudges, such as the introduction of decoy plans, can lead to more profitable consumer behaviors. For marketers and platform managers, leveraging behavioral economics concepts like the attraction effect can lead to more effective pricing models that not only increase immediate sales but also improve long-term consumer engagement. The psychological underpinnings of this strategy make it a powerful tool for optimizing customer decision-making processes.

5.2. Limitations and future prospects

The limitations of this study can be categorized into two major areas. First, the data used in this study only covers the two months following the intervention, so the long-term impact on consumer behavior and attitudes remains unclear. The influence of the intervention over longer periods, such as a year, would be of great practical interest to marketers and researchers. Therefore, research focusing on the long-term effects holds significant value.

Second, the study's generalizability can be partially influenced by the unique characteristics of the service, which involves a high degree of fan engagement. While the findings have contributed to understanding the decoy effect in digital marketplaces to some extent, the applicability of the results to more general products or services should be approached cautiously. In light of these limitations, further studies are encouraged, particularly in real-world contexts, to better understand the attraction effect under different circumstances.

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