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Understanding Customer Participation Dynamics: The Case of the Subscription Box

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Abstract

Although subscription boxes are incredibly popular, box companies often miss out on the benefits of a subscription model. Customers routinely skip boxes, and even when they do not, they often return products from each box. Hoping to avoid these returns, box companies ask customers to preview upcoming boxes, evaluate delivered boxes, and justify skipped boxes. The authors are interested in how such extensive customer participation can discourage skipping or, even better, encourage spending. An analysis of 30,000 apparel box customers' repeated preview, feedback, and purchase behavior reveals that, in addition to *whether* customers participate, *the way* in which and *when* they participate matter, and often in counterproductive ways. Specifically, customer participation with the delivered box drives future purchases, whereas participation before and after the delivered box appears to decrease box opt-in and spending. Further, the double-edged nature of customer participation, especially when such participation involves emotionality, has long-lasting effects, indicating the important role of customer participation dynamics in shaping purchase behavior.

Keywords

subscription box, customer participation, customer journey, dynamics, text analysis

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The subscription box is a popular ecommerce model. Companies curate boxes of products, including apparel, meal kits, tech gadgets, personal care, and toys, and deliver them to customers' doorsteps at regular intervals. For product companies, this is their opportunity to gain the type of recurring revenue enjoyed by service companies (Andonova, Anaza, and Bennett 2021). Further, they gain rich data from digital interactions with customers that they can use to improve their personalized offerings. This business model has enticed established retailers, such as Sephora, Walmart, Nordstrom, and Target, to develop their own subscription boxes as a means to compete with hundreds of newcomers, including Birchbox and Stitch Fix, whose combined current valuation is roughly $1 billion. For customers, subscription boxes offer an easy, convenient, and consistent way to access product variety with little commitment. They can skip a box anytime or return the box's products every time. Although such flexibility is attractive (50% of online shoppers subscribe to at least one box; Panko 2019), its consequences are concerning for box companies. Customers frequently skip boxes, and even when they do not, they return 60%–70% of the box's products (Van Pelt 2018). Notably, Nordstrom and Target have since shut down their subscription boxes, and although Sephora continues to offer one, it and other retailers, have become concerned about "box fatigue" (Simeon 2020; Thomas 2022). It is clear that getting the subscription box model to work for the company is challenging.

Hoping to improve their outcomes, box companies involve customers throughout the box process, using a series of digital touchpoints. Customers are invited to digitally preview an upcoming box, offer feedback about the products in a delivered box, and provide reasons for skipping a box. The idea is that, in addition to learning about customers' tastes, having them actively participate in the box process is engaging, which, in turn, should result in less skipping and more spending. There is support for this idea, but only for part of it. Participation behavior is indeed engaging, empowering, and

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entertaining for customers, leading to higher satisfaction (Auh et al. 2019; Chan, Yim, and Lam 2010); however, whether customer participation translates into objective outcomes that benefit companies remains unclear. There is little empirical evidence in the customer participation literature that participating customers change their purchase behavior. This is because customer participation has been difficult to measure and even more so to tie to individual behavior. Given the increasing digital footprint of evolving customer–firm interactions, however, this has become possible, especially for repeated transactions over time (Schweidel et al. 2022). As a result, companies have gained a gold mine of panel data on recurring customer participation and purchase behavior. Leveraging this, we assess the effect of customer participation on purchases not only in regard to the next box but also in terms of the next several boxes. As such, we capture the role of customer participation dynamics in driving box purchases.

We also understand, however, that customers do much more than simply participate. Customers express opinions and reactions in certain emotional ways, which can be more informative than their simply rating how happy or unhappy they are (Berger et al. 2020; Rocklage, Rucker, and Nordgren 2021). Linguistic emotionality in, for example, online reviews has been shown to persuade others and increase product interest (Rocklage and Fazio 2020). Customers also provide concrete and detailed feedback with tangible examples and suggestions. Linguistic concreteness signals attentiveness and trustworthiness, both of which are perceived favorably by others (Packard and Berger 2021; Schellekens, Verlegh, and Smidts 2010). Although it is clear that linguistic emotionality and concreteness have an impact on others' behavior, it is not clear whether they affect the expressing customer's own behavior. Work in this nascent area suggests that this may be the case (e.g., Rocklage, Rucker, and Nordgren 2018), but there is no evidence to support it. We also wonder whether having customers participate, especially in emotional or concrete ways, has the potential to backfire. We argue that whether customers participate, including the way such participation is expressed, can affect future box purchases differently, depending on when, in the customer journey, the customer participates. The customer journey consists of prepurchase, purchase, and postpurchase stages (Lemon and Verhoef 2016), which map onto the upcoming, delivered, and skipped box stages of the box process, respectively. Although involving customers in the upcoming box by having them preview its contents (and make changes if needed) may increase the odds of the success of that box, it has the potential to ruin the "surprise" element coveted by customers (Andonova, Anaza, and Bennett 2021; Van Pelt 2018), which may affect future purchases. Customer participation with the delivered box and its tangible products can be considered an engaging activity relative to participating with a skipped box and its hypothetical products (i.e., the customer's providing feedback about why they are skipping). Further, customer participation regarding future box purchases is related to the extent to which the customer is engaged with the box.

We examined these possibilities using secondary data from a national apparel box company that included approximately 30,000 customers' repeated participation, closed- and open-ended feedback, and box purchase behaviors from 2015 to 2018. We used natural language processing (NLP) software to mine customers' open-ended feedback to measure linguistic emotionality and concreteness. We jointly modeled customers' monthly box opt-in and box spending as a function of accumulated customer participation while correcting for endogeneity bias and accounting for observed and unobserved heterogeneity. Our model also accounts for how customer participation history and past purchase behavior affect individuals over time by specifying decay parameters estimated using Bayesian methods. The estimation results reveal that customer participation has a significant and persistent effect on customers' future box purchase behavior. Specifically, in terms of short- and long-term effects of customer participation on future box purchases, the results related to participating with (1) the upcoming box are negative, (2) the delivered box are positive, and (3) the skipped box are negative. Further, the concreteness or emotionality of participation reinforce these effects, for example, by making customer participation with the delivered box more positive and with the skipped box more negative. Finally, the impact of participation concreteness is immediately larger than emotionality, whereas participation emotionality persists longer.

The findings of this research provide four important contributions. First, customer participation has been difficult to measure, largely because digital footprints were not available in the past. Thus, researchers could capture only whether the company offered the touchpoint rather than whether the customer actually used the touchpoint; thus, the customer's past action was inferred from the company's past action (e.g., Van Diepen, Donkers, and Franses 2009). In other cases, researchers used customers' recollected participation (from a survey) or induced participation (using experiments) to measure customer participation (e.g., Auh et al. 2019; Blut, Heirati, and Schoefer 2020). Although the results of this research were insightful, such approaches may omit certain types of participation or participation altogether if it occurred a long time ago. We add to this body of work by leveraging objective behavioral measures of customer participation to explain real purchase behavior.

Second, we broaden the current understanding of customer participation beyond *whether* customers participate to *the way* they participate by leveraging advances in computational linguistics. Although prior work has focused on how linguistic emotionality (Rocklage, Rucker, and Nordgren 2018) or concreteness (Packard and Berger 2020; Schellekens, Verlegh, and Smidts 2010) affects the behavior of others, we demonstrate that these linguistic considerations also affect the expressing person's own behavior. Further, we capture both linguistic devices in a single framework, enabling us to compare their effects, which has not been done before.

Third, we are the first to capture customer participation dynamics. Previously, capturing dynamics has usually meant relating the company's past actions to the customer's present behavior (e.g., Schweidel and Knox 2013; Van Diepen,

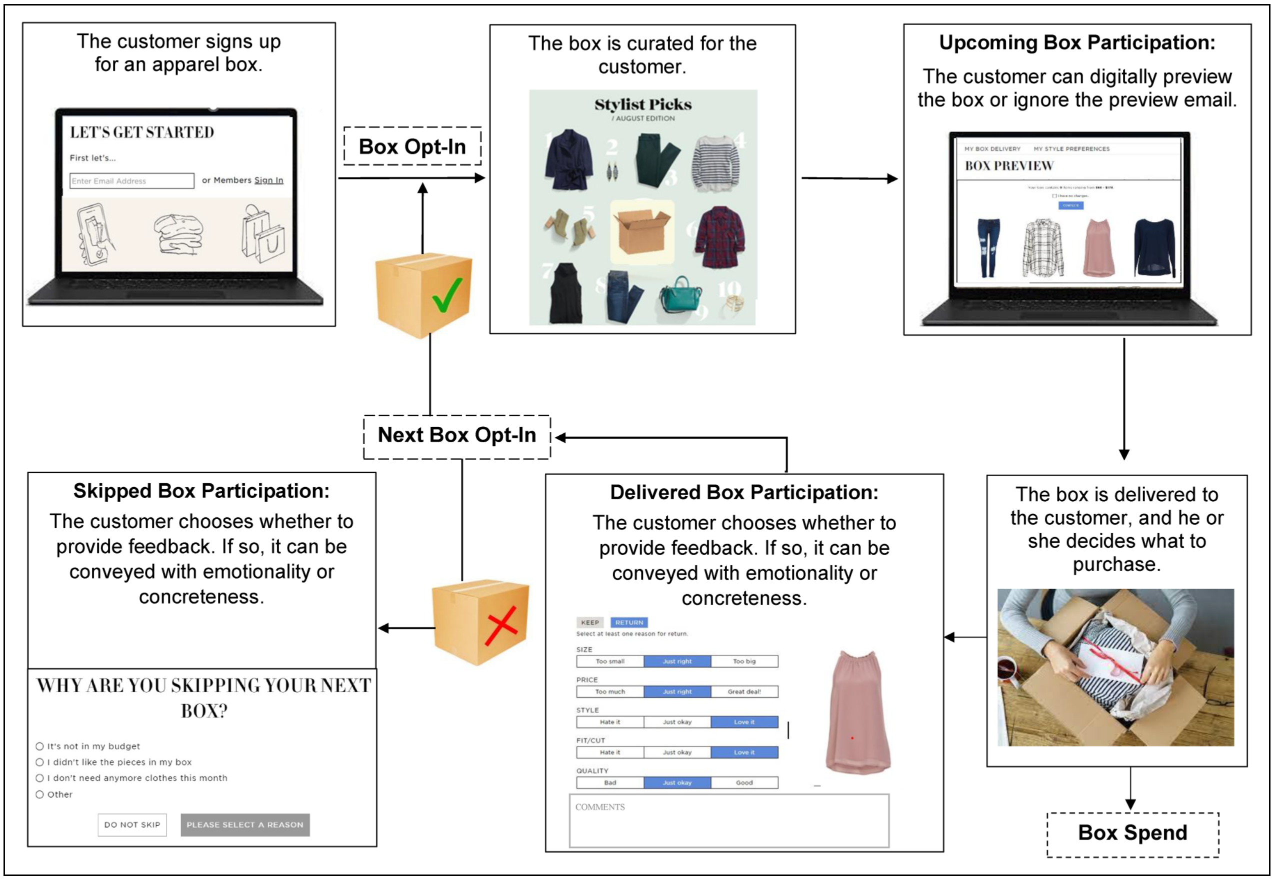

Figure 1. Subscription Box Journey of Customer Participation.

Donkers, and Franses 2009). The few studies (e.g., Knox and Van Oest 2014; Van Oest and Knox 2011) that related customers' past actions to their present behavior have focused entirely on complaints, reflecting negative sentiment rather than customer participation. We disentangle participation from sentiment to isolate the long-term effect of the participation behavior alone. Further, we add to prior work on customer journey mapping (e.g., De Keyser et al. 2020; Lemon and Verhoef 2016) by showing that the effect of customer participation flips signs as it progresses through stages of a single box process.

Fourth, our findings have clear substantive implications for managing customer participation, especially for box companies. To the best of our knowledge, this is the first study in marketing to focus on the subscription box, one of the most popular retail models of the last decade. We make recommendations using counterfactual and simulation analyses that quantify the financial impact of customer participation. Our findings suggest that box companies should be cautious about encouraging customers to participate with upcoming boxes because, overall, doing so lowers box purchases. Had our partner box company limited upcoming box participation instead of encouraging it, it would have gained 14% in customer lifetime revenue (CLR). Box companies should, however, encourage emotional and concrete feedback about delivered boxes. Finally, we caution the overuse of box skipping as an opportunity to learn from customers by assuming that feedback is "free." Rather, it costs the company by lowering future box purchases, especially when customers provide concrete feedback, making box skipping doubly damaging. Had the partner box company not encouraged customers to provide concrete and specific reasons for skipping a box, it would have gained 10% in CLR.

We begin the next section by discussing the subscription box process established by our collaborating firm and develop our hypotheses. We then describe our secondary data, followed by the modeling and estimation approaches. We present the results of our model estimation and outline the implications for theory and practice, including specific recommendations for box companies. We end by acknowledging our limitations, which offer directions for future research.

The Box Process

Consider the customer who signs up for a subscription box to receive monthly deliveries of apparel and accessories (Figure 1). The box company curates seven to nine products for the customer's first box but, before shipping it, emails the customer with the opportunity to digitally preview the box, view its contents (upcoming box participation), and modify it, if needed. The box is then shipped to the customer. After receiving the box and trying on its items, the customer completes a digital checkout to purchase products and/or initiate returns. If every product is returned, then the customer is charged a curation fee, but if the customer keeps at least one item, the fee is applied toward the price of the item. The customer is then asked to provide feedback about the products, using drop-down menus and open-ended text boxes (delivered box participation) before completing the digital checkout. Before the next box is curated, the customer chooses whether to accept the scheduled box or skip it. If the customer chooses to skip it, they are asked to provide reasons for skipping using a drop-down menu and an open-ended text box (skipped box participation).

Thus, each month, the customer makes two decisions: whether to receive the box and, conditional on deciding to receive the box, how much to purchase from it. In forming our hypotheses, however, we consider these decisions together as box purchases because, a priori, we have no reason to believe that customer participation would affect them differently.[1] Next, we hypothesize how customer participation, including the way customers participate, at different stages has an impact on future box purchase behavior.

Theory and Hypotheses

Customer participation occurs when the customer takes part in the creation, delivery, or review of the product (Chan, Yim, and Lam 2010). Customer participation is thus a behavior, which we isolate from the content of participation, such as what participating is intended for or is about. For example, choosing to cocreate the product is the participation behavior, whereas the particular changes made to the product is the content of participation. Similarly, providing feedback about the product is the behavior, whereas the sentiment (praising or complaining) or details embedded in the feedback (the quality and price of the product) is the content of participation. We are interested in whether the mere act of participating with a product has implications for the customer's future box purchases.

In general, the literature has viewed customer participation positively. It generates intangible benefits, such as enjoyment (Yim, Chan, and Lam 2012) and empowerment (Auh et al. 2019), and has been linked to perceptions of quality and feelings of commitment to the company (Chan, Yim, and Lam 2010). Although the notion is untested, such benefits should translate into more purchases from the company. However, this may not always be true. Customer participation can backfire if the customer is given too tedious a task (e.g., coming up with product solutions while cocreating with the company; Blut, Heirati, and Schoefer 2020; Haumann et al. 2015). Irrespective of participation effort, however, we expect that whether customer participation increases or decreases future box purchases will depend on which stage in the box process the participation occurs.

[1] Although we do not hypothesize differences between box opt-in and box spending, in case differences arise, we estimate separate short-term and long-term effects of customer participation for each.

Customer Participation During Stages of the Box Process

The customer journey refers to the path of customer–company interactions for a particular purchase (Lemon and Verhoef 2016), which, in this case, is a box. The interactions occur over different stages, which include prepurchase (upcoming box), purchase (delivered box), and postpurchase (skipped box) stages. Each stage is viewed as an opportunity to gather information or rectify a wrong, while also engaging the customer (De Keyser et al. 2020). Typically, the prepurchase stage involves the customer's recognizing a need, searching for products that address that need, and evaluating options (Lemon and Verhoef 2016). The responsibility is given to the customer to form the consideration set. For subscription boxes, however, the curator and the box company are responsible for forming the customer's consideration set of products from which to choose. Shifting responsibility adds considerable uncertainty, so box companies encourage customers to preview the upcoming box and suggest changes, if needed.

By involving the customer, however, the company risks depriving them of some of the value sought in the product. This occurs when the company does the work, instead of the customer (Dong et al. 2015), which detracts from the enjoyment of the moment of surprise when the box would have arrived with unfamiliar, but personally curated, products. Research shows that customers enjoy the sense of novelty associated with curated box services and the anticipation of being surprised by the box's contents (Andonova, Anaza, and Bennett 2021; Van Pelt 2018). Indeed, 55% of box subscribers choose surprise-based curation boxes rather than preselected ones (Anderson 2020). Thus, although customer participation with the upcoming box may increase spending with that particular box, by preventing the customer from being surprised and experiencing novelty, the company risks undermining the underlying business model of subscription boxes and, thus, could decrease the customer's desire to engage with the next box.

During the purchase stage, customers choose which product to buy, how to pay for it, and how to receive it (De Keyser et al. 2020), but only after having interacted with the product enough to make these choices. The customer physically receives the delivered box, opens it, and tries on clothes (e.g., for an apparel box). Irrespective of whether the customer likes each product, interacting with the products in the comfort of their home is engaging. The box's contents are no longer a digital depiction but rather a tangible reality that is under the customer's control. These are the hallmarks of the customer experience and relationship-building (Zeithaml, Berry, and Parasuraman 1996). If then asked to provide feedback about each product, through participating, the customer solidifies their engagement with the company (Lemon and Verhoef 2016), the result of which should be more box purchases in the future.

If we then compare this scenario with one that involves a skipped box in the postpurchase stage, a different outcome should emerge. Skipping a box is a clear indication to both the customer and the company that the customer is delaying the relationship. Further, the skipped box is both hypothetical and temporally distant, causing the customer to miss out on the value of tangibility and proximity (Zeithaml, Berry, and Parasuraman 1996) made possible by a delivered box. Thus, regardless of the reasons for box skipping (e.g., being dissatisfied with the last box, personal reasons such as going on a trip or moving), the stage itself is inherently disengaging. If then asked to detail reasons for skipping the box, by participating, the customer solidifies their disengagement with the company (Kumar and Pansari 2016), the result of which should be fewer box purchases in the future. Therefore,

H_{1a}: Customer participation with an upcoming box has a negative effect on future box purchases.

H_{2a}: Customer participation with a delivered box has a positive effect on future box purchases.

H_{3a}: Customer participation with a skipped box has a negative effect on future box purchases.

The Way Customers Participate: Emotionally and Concretely

Let us assume that the customer provides feedback in all three stages of the box process. Normally, such feedback would be mined for how positive or negative its sentiment is. Recently, however, researchers have begun to question the value of sentiment in predicting behavior (Rocklage, Rucker, and Nordgren 2021), implying that other aspects of emotion embedded in feedback are indicative of future behavior. Further, because customers intellectualize their experiences with brands (Brakus, Schmitt, and Zarantonello 2009), companies mine feedback for specific topics and suggestions to capture cognition, or what the customer thinks of the product (Ordenes et al. 2014). The customer's providing several details, however, may alone do little to predict future behavior. Rather, *the way* that customers convey feedback is consequential.

Two aspects of content delivery that capture attention are emotionality (reflecting the way that emotions are delivered) and concreteness (reflecting the way that information is delivered) (Pogacar, Shrum, and Lowrey 2018; Rocklage, Rucker, and Nordgren 2018). Emotionality refers to the extent to which a person's attitude is based on feelings and emotion. The same sentiment (the customer has a positive impression of the jacket) can be delivered less emotionally ("The jacket is nice") or more emotionally ("I love this jacket!"). The more that people express their feelings with emotionality, the more likely others are to notice. Customers thus use more emotional language online when they want to persuade others (Berger, Kim, and Meyer 2021). Further, when customers express stronger emotions, they signal to themselves that something important has happened, which makes the emotion self-reinforcing (Rocklage, Rucker, and Nordgren 2018). Greater emotionality in customer reviews, for example, has been shown to correlate with product sales (Ludwig et al. 2013; Rocklage, Rucker, and Nordgren 2021). Rather than assuming a positive relationship, we expect that whether customer participation with more emotionality drives or limits future box purchases depends on when the participation occurs in the box process.

Further, the same information can be delivered less concretely ("The fit of the jacket is just right") or more concretely ("The jacket has a nice contour and a clean drape"). Whereas less concrete language captures intangible qualities or concepts, concrete language captures tangible and immediate experiences (Brysbaert, Warriner, and Kuperman 2014). Concrete descriptions are comprehended, imagined, and recalled more easily, causing others to perceive concrete information as more truthful (Hansen and Wänke 2010). Information delivered concretely can also signal attentiveness to others, leading receivers of the information to be more satisfied (Packard and Berger 2021).

We expect emotional or concrete customer participation in regard to the upcoming, delivered, or skipped box to amplify the effects hypothesized in H_{1a}–H_{3a}. To reiterate, if the customer previews the box and provides emotional or concrete feedback about the previewed products, then not only has the element of surprise been removed, but also the very aspects that the customer wanted to be surprised by have already been described in detail, thereby eliminating the element of novelty. Argued similarly, but in the opposite direction, when engaging with the delivered box, the customer's offering emotional or concrete feedback about the products in plain view should reinforce customer engagement, leading to future box purchases. Finally, applying the same logic to box skipping, choosing to disengage with the company (at least momentarily) and making the effort to describe why using emotionality or concrete details is likely to reinforce the disengagement and lead to fewer box purchases in the future. Thus,

$P_{1b–c}$: For an upcoming box, customer participation that is more (b) emotional or (c) concrete has a negative effect on future box purchases.[2]

$H_{2b–c}$: For a delivered box, customer participation that is more (b) emotional or (c) concrete has a positive effect on future box purchases.

$H_{3b–c}$: For a skipped box, customer participation that is more (b) emotional or (c) concrete has a negative effect on future box purchases.

We depict the conceptual framework in Figure 2.

Empirical Context and Variable Measurement

We tested our hypotheses using data from a national apparel subscription box company. The company curates boxes of apparel products and delivers them to customers each month. Customers are charged a $40 curation fee for each box. This fee was applied toward the purchase of at least one product in the box, but if customers returned everything, they were charged

[2] We did not hypothesize this relationship because the data to test it are unavailable. Still, because we expect the relationship to exist, we state a proposition instead of a hypothesis and encourage future researchers to test it if the data become available.

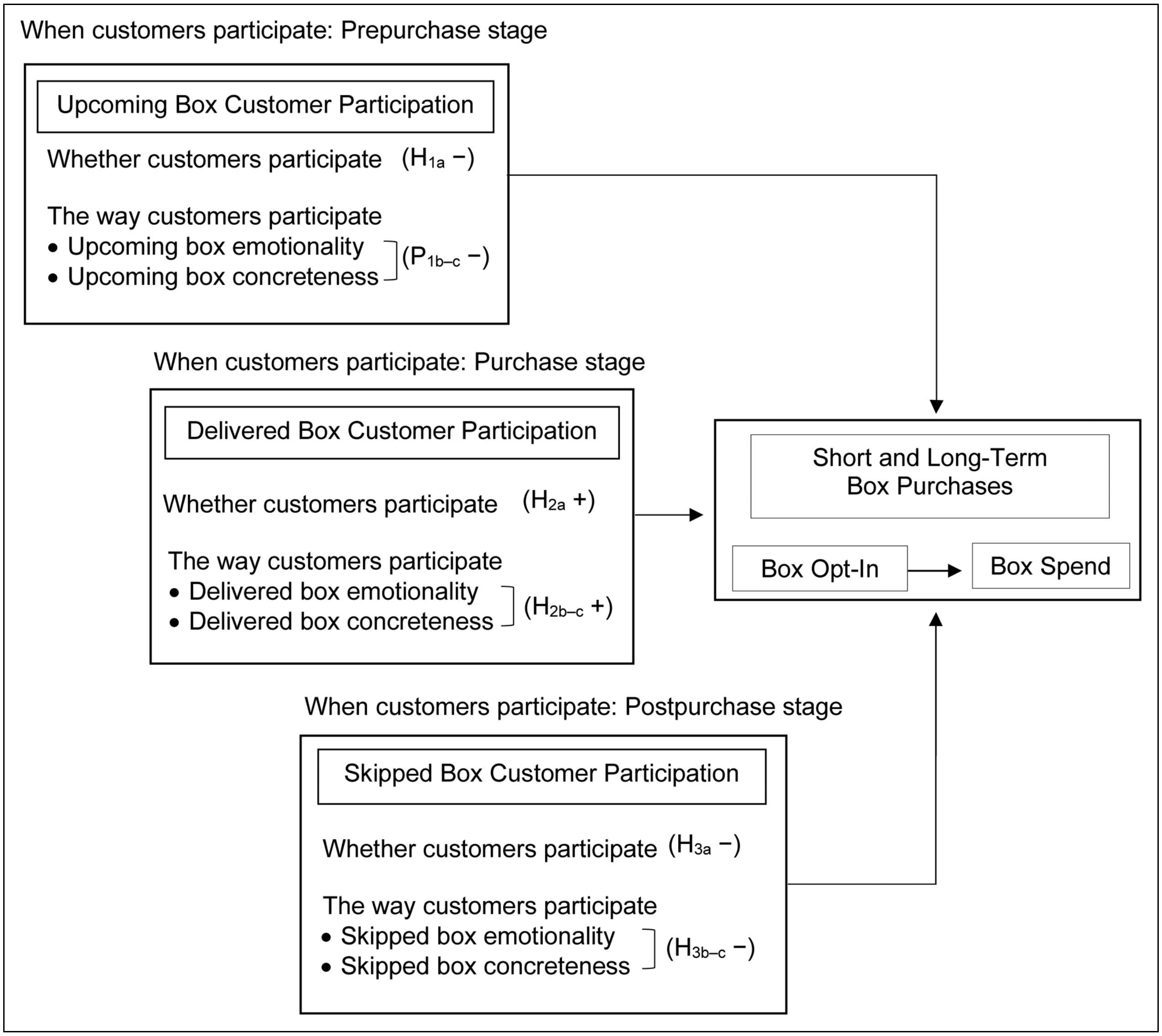

Figure 2. Conceptual Framework.
Notes: The hypothesized effects of customer participation on box purchase outcomes are displayed in parentheses. They indicate the direction of the effect, where "−" indicates a negative effect and "+" indicates a positive effect. P_{1b-c} refers to a proposition, rather than hypothesis, because the data to test it are not available.

the curation fee. The company enabled customer participation using the digital touchpoints depicted in Figure 1. Every purchase transaction and customer participation interaction occurred digitally, enabling us to collect rich structured and unstructured data for each box. We constructed a panel of monthly transaction and customer participation histories from November 2015 to May 2018 for approximately 52,000 customers. The data spanned over 30 months, and a sizeable percentage of customers canceled their subscription after just one box (21,944 customers; 42.23%). Because we were interested in capturing customers' participation dynamics, we restricted our sample to customers who purchased at least two boxes, resulting in an unbalanced panel of 30,017 customers and 108,131 box purchases. We describe our monthly measures of customer participation and box purchases next and summarize them in Table 1.

Dependent variables. Every month, the customer makes two decisions: whether to continue to receive a box (vs. skip one shipment) and, if so, how much to buy from that box. Using standard nomenclature, we defined box opt-in_{it} as customer i's decision to get the box in month t (opt-in = 1, opt-in = 0) and box $spend_{it}$ as the amount ($) customer i spends on the box in month t while keeping in mind that only when box opt-in_{it} = 1 can box $spend_{it}$ > 0. Box spend was skewed, so we log-transformed this variable. On average, customers ordered 3.6 boxes (SD = 2.57 boxes), spent $154.9 on each box (SD = $178.9), and skipped 2.3 boxes, resulting in a box-skip rate of 39.2%.

Independent variables. Given that we measured our dependent variables for the box in month t, we observed our independent variables that relate to customer participation for the previous

Table 1. Variables and Measures.

Construct	Variable	Measure
	Dependent Variable	
Purchase behavior	Box opt-in$_{it}$	Customer i opted into the box (vs. skipped the box) in month t.
Purchase behavior	Box spend$_{it}$	Customer i's ($; log-transformed) amount spent on the box in month t.
	Customer Participation	
Customer participation	Upcoming box participation$_{it-1}$	1 = customer i digitally previewed the box in month t−1; 0 = customer i did not preview.
Customer participation	Delivered/skipped box participation$_{it-1}$	1 = customer i used the drop-down menu or open-ended text box in month t−1; 0 = customer i did not participate.
Linguistic emotionality	Delivered/skipped box emotionality$_{it-1}$	Score of emotionality from NLP of the open-ended text provided by customer i about the delivered/skipped box in month t−1.
Linguistic concreteness	Delivered/skipped box concreteness$_{it-1}$	Score of concreteness from NLP of the open-ended text provided by customer i about the delivered/skipped box in month t−1.
	Control	
Past purchase behavior	Purchase ratio$_{it-1}$	Number of products purchased by customer i divided by total number of products in the box in month t−1.
Box cocreation	Upcoming box modification$_{it-1,t}$	1 = customer i requested changes to the box in month t−1 or t, 0 = customer i did not.
Word count	Delivered/skipped box word count$_{it-1}$	Number of words of open-ended text provided by customer i about the delivered/ skipped box in month t−1.
Sentiment	Delivered/skipped box positivity$_{it-1}$	Difference between positive and negative sentiment scores from NLP of open-ended text provided by customer i about the delivered/skipped box in month t−1.
Relationship duration	Customer tenure$_{it}$	Number of months since customer i's first purchase until month t.
Box value	Box retail value$_{it}$	Total (log-transformed) retail value of a box of products sent to customer i in month t ($).
Service provider turnover	New curator$_{it}$	1= if customer i was assigned a new curator in month t, 0 = the curator did not change.
Service provider quality	Curator performance$_{it-1}$	Average ($) sales across customers generated by the curator assigned to customer i in month t−1.

Notes: NLP = natural language processing. We used the NLP tool TextAnalyzer (Berger, Sherman, and Ungar 2020).

box in month t−1. We lagged our customer participation variables for a few reasons. First, in any month, box opt-in occurs before customer participation for that box, so the box opt-in decision can be driven only by customer participation with the previous box(es). Second, because customers provide delivered box feedback *after* they decide what they are purchasing versus returning from the delivered box, such participation should be tied only to the next box's purchases. Third, skipped box feedback cannot be linked with box purchases in month t because it is a skipped box and, thus, can affect only subsequent box purchases.

Using a dichotomous scale to measure upcoming box participation, we assigned a value of 1 if the customer opened the preview email and a value of 0 if they did not. Customers previewed the upcoming box 61.9% of the time.

During digital checkout, the customer can choose to use drop-down menus to rate apparel attributes, including size, price, style, fit, and quality. The customer also can leave feedback using open-ended text boxes. Using a dichotomous scale to measure delivered box participation, we assigned a value of 1 if the customer participated in any form of feedback (used the drop-downs and/or provided open-ended feedback) and a value of 0 if they did not. Customers used at least one drop-down menu 74% of the time and provided open-ended feedback 46% of the time, writing a mean of 44.8 words. Further, we analyzed the open-ended text using the NLP tool TextAnalyzer (Berger, Sherman, and Ungar 2020). We measured delivered box emotionality using the NLP tool's output for the lexicon "emotionality" (range of values: 0 to 9; Rocklage, Rucker, and Nordgren 2018). Examples of lower emotionality (higher emotionality) include "I don't need this right now" and "The straps were loose" ("I hate wearing this" and "I really love the detail on the bottom"). Average delivered box emotionality was 3.94 (SD = 2.83, range = 0 to 8.26). We measured delivered box concreteness using the NLP tool's output for the lexicon "concreteness" (range of values: 100 to 700; Paetzold and Specia 2016). Examples of lower concreteness (higher concreteness) include "It is not for me" and "I own something similar" ("I don't like the tie in back" and "I am not a fan of skinny jeans"). Average delivered box concreteness was 330.36 (SD = 22.46, range = 182.51 to 654.60). We standardize these variables to compare their effects subsequently.

If the customer skipped a box in month t, which occurred 39.2% of the time, then they could decide whether to provide a reason for skipping (which occurred for 14% of skipped boxes). The customer could indicate the main reason by selecting from a prepopulated drop-down menu with three reasons ("It's not in my budget," "I don't need any more clothes this month," and "I didn't like the pieces in my box") or by describing it using an open-ended text box. We used a dichotomous variable to measure skipped box participation and assigned a value of 1 if the customer used the drop-down menu or provided open-ended feedback and a value of 0 if they did not provide feedback. The drop-down menu was used 88% of the time, and the remaining 12% was used for open-ended feedback, averaging 7.37 words (SD = 6.20, range = 1 to 60). We analyzed the open-ended text using the TextAnalyzer tool described previously. An example of lower emotionality (higher emotionality) included "Not for me" ("I hate your service"). Average skipped box emotionality was .29 (SD = 1.22, range = 0 to 8). An example of lower concreteness (higher concreteness) included "I am not interested" ("I am traveling this month"). Average skipped box concreteness was 342.39 (SD = 27.36, range = 0 to 509.42). We standardized the variables to allow us to compare their subsequent effects.

Additional covariates. To isolate the effect of customer participation on box purchases, it was important to create temporal distance between the two events such that customer participation with the box in month t−1 was related to box purchases in the following month t. Upcoming box participation for box t, however, occurs before the box spend decision for that box, so it was important to control for its contemporaneous effect on the previewed box's spend. Further, because the customer was able to modify the previewed box by suggesting changes (capturing customization and cocreation), we controlled for the effect of upcoming box modification for the box in month t−1 on box spend for that box as well as the next box's purchases. We used a dichotomous scale to assign a value of 1 if the customer modified the box and a value of 0 if they either did not preview the box or previewed it but did not modify it. We controlled for the impact of customer satisfaction with the box in month t−1 on the next box' purchases by measuring purchase ratio, the percentage of products purchased (vs. returned) from box t−1.

We also controlled for the effects of delivered box word count and delivered box positivity mined from open-ended text for box t−1 using the NLP tool's output for word count and the lexicon "sentiment" (Kiritchenko, Zhu, and Mohammad 2014). The percentage of negative words was subtracted from the percentage of positive words to create the positivity measure. Similarly, we measured skipped box word count and skipped box positivity by mining the skipped box open-ended text. We measured customer tenure as the number of months since the customer made the first purchase. Further, because box spend in month t is not only a function of what the customer chooses to buy but also the retail value of the products included in that box, we included the log-transformed variable, box retail value. We also obtained data on the curator assigned to each box, which, for a given customer, is typically the same across boxes. If the curator happens to change (by leaving the company or being reassigned), however, then we controlled for new curator by assigning a value of 1 if the curator changed and a value of 0 if the curator was the same as before. Finally, we controlled for curator performance by averaging the sales generated by the curator across customers in the previous month. We provide the descriptive statistics and a correlation matrix of the dependent variables and customer participation measures in Table 2 (the comprehensive table, which includes all variables used in our model, is provided in the Web Appendix A).

Modeling Framework and Estimation

Model Setup

We were interested in measuring the effects of customer participation on subsequent box purchase decisions. Box purchase decisions involve two related, but distinct, purchase outcomes: box opt-in and box spend. The customer first decides whether to agree to the next box and, if so, after receiving the box, how much to spend on it. We used a Type II Tobit model to jointly estimate box opt-in and box spend and accommodate the conditional nature of box spend. We began with two general models, one for each box purchase decision. We assumed that box opt-in$_{it}$ for customer i and the box in month t was based on the following continuous latent variable:

$$\text{Box opt-in}^*_{it} = \gamma X_{\text{opt-in},it-1} + \varepsilon_{\text{opt-in},it}, \tag{1}$$

with opt-in$_{it}$ = 1 if opt-in$_{it}$* > 0 and opt-in$_{it}$ = 0 if opt-in$_{it}$* ≤ 0. opt-in$_{it}$* is a function of the row-vector of predictor variables, $X_{\text{opt-in},it-1}$, the column-vector of parameters, γ, and the random error, $\varepsilon_{\text{opt-in},it}$. We assumed that box spend$_{it}$ for customer i and the box in month t is based on the following continuous latent variable:

$$\text{Box spend}^*_{it} = \zeta X_{\text{spend},it-1} + \varepsilon_{\text{spend},it}, \tag{2}$$

with spend$_{it}$ = spend$_{it}$* if opt-in$_{it}$ = 1 and spend$_{it}$ = 0 if opt-in$_{it}$ = 0. spend$_{it}$* is a function of the row-vector of lagged predictor variables, $X_{\text{spend},it-1}$, the column-vector of parameters, ζ, and the random error, $\varepsilon_{\text{spend},it}$.

When capturing the interdependence between box opt-in and box spend, we assumed that the random error terms in Equations 1 and 2 were normally distributed and correlated. We fixed the variance of the error term for box opt-in for model identification:

$$\begin{pmatrix} \varepsilon_{\text{opt-in},it} \\ \varepsilon_{\text{spend},it} \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho\sigma \\ \rho\sigma & \sigma^2 \end{pmatrix}\right]. \tag{3}$$

Please note that $X_{\text{opt-in},it-1}$ and $X_{\text{spend},it-1}$ are the vectors of predictor variables, including our focal customer participation variables (upcoming box participation, delivered box participation,

Table 2. Descriptive Statistics and Correlation Matrix for Dependent and Key Customer Participation Variables.

Variable	Mean	SD	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1. Box opt-in (0/1)	.53	.50	1								
2. Box spend ($)	154.91	178.92	N.A.	1							
3. Upcoming box participation	.36	.48	.03**	−.02**	1						
4. Delivered box participation	.45	.50	.08**	.02**	.25**	1					
5. Delivered box emotionality	1.20	2.41	.07**	.07**	.24**	.35**	1				
6. Delivered box concreteness	158.37	151.53	.08**	.08**	.28**	.34**	.41**	1			
7. Skipped box participation	.06	.24	−.06**	−.11**	.10**	.17**	.06**	.08**	1		
8. Skipped box emotionality	.09	2.10	−.01**	−.01**	.003	.01**	.01	.01	.08**	1	
9. Skipped box concreteness	120.94	82.37	−.20**	−.10**	.10**	.17**	.06**	.09**	.15**	.07**	1

**p < .01.
Notes: N = 147,760; N.A. = not applicable.

delivered box emotionality, delivered box concreteness, skipped box participation, skipped box emotionality, and skipped box concreteness). In general, we included the same predictors in the two vectors because, from a theoretical perspective, we had no reason to think that box opt-in and box spend were driven by different factors. Before continuing with our analysis, however, we augmented the focal customer participation variables to enable us to capture their long-term effects.

Stock measures to capture dynamics. When structuring the data, we aligned customer i's purchases with the box in month t with the participation with the box in month t−1. We also wanted to consider the case in which customer i also participated with the box in months t−2, t−3, and in the months before. If this were the case, then the box purchase in month t could easily have been affected by cumulative participation from all of the previous months, t−1 to t−n. The notion that today's behavior is affected by an accumulation of past actions is known as dynamics. To assess whether customer participation dynamics exist in our data, we created cumulative, or stock, measures using a validated method (e.g., Schweidel and Knox 2013; Van Diepen, Donkers, and Franses 2009). We updated the stock measures each month to include the current month's customer participation and the stock of customer participation from the previous months. We offer a generic example of stock variable construction as follows:

$$\text{Stock customer participation}_{it-1} = \text{Customer participation}_{it-1} + \lambda \text{ Stock customer participation}_{it-2}. \tag{4}$$

We estimated this decay parameter (λ) to account for the diminishing impact of customer participation that occurred previously, capturing notions of both memory and forgetting. We logit-transformed the decay parameters to constrain them between 0 and 1. Considering the seven customer participation variables, we needed to estimate seven decay parameters, λ_1 to λ_7. Finally, because past purchase habits affect current purchases (Van Diepen, Donkers, and Franses 2009), we created a stock measure of purchase ratio, resulting in the eighth decay parameter, λ_8. Before estimating the models with the stock measures, however, we tried to eliminate sources of endogeneity bias, which we describe next.

Addressing potential endogeneity bias. We lagged the independent variables by one month to force temporal ordering between the independent and dependent variables to rule out reverse causality. Some customers interact with companies more extensively than do others due to unobservable factors, such as personality or expertise, rendering the customer participation variables endogenous. To address this, we controlled for unobserved customer heterogeneity using normally distributed random effects, which for customer i was $\alpha_i \sim N(a, \Sigma_\alpha)$. Further, customer i's decision to participate in each stage may be nonrandom, leading to problematic correlations between the observed variables and error terms. To address this, we estimated m Gaussian copulas (Park and Gupta 2012) where m = 3, representing the three (discrete) participation variables—upcoming box participation$_{it-1}$, delivered box participation$_{it-1}$, and skipped box participation$_{it-1}$—as follows:

$$\text{Discrete customer participation copula}_{mit-1} = \Phi^{-1}[U_m(\text{Discrete customer participation}_{mit-1})], \tag{5}$$

where $\Phi^{-1}(\cdot)$ is the inverse normal cumulative distribution function and $U(\cdot)$ is uniformly distributed within [0,1]. We integrated the three copulas into Equations 1 and 2.

We also included Z, an n × K matrix, with K representing the vector of control variables described in Table 1. For the box spend model, K also included the additional variable, box retail value in month t. Finally, we included month and year fixed effects to control for seasonality and unobserved actions by the sample company. Our final specification for $\gamma X_{\text{opt-in},it-1}$ and for $\zeta X_{\text{spend},it-1}$ in Equations 1 and 2, including the estimated decay parameters in Equation 4 and the copulas in Equation 5, was:

$$
\begin{aligned}
&= \beta_1 \text{Stock upcoming box participation}_{t-1}\\
&+ \beta_2 \text{Stock delivered box participation}_{t-1}\\
&+ \beta_3 \text{Stock skipped box participation}_{t-1}\\
&+ \beta_4 \text{Stock delivered box emotionality}_{t-1}\\
&+ \beta_5 \text{Stock delivered box concreteness}_{t-1}\\
&+ \beta_6 \text{Stock skipped box emotionality}_{t-1}\\
&+ \beta_7 \text{Stock skipped box concreteness}_{t-1}\\
&+ \beta_8 \text{Stock purchase ratio}_{t-1}\\
&+ \delta \Sigma_m \text{Customer participation copula}_{mit-1}\\
&+ \Theta Z_{it-1} + \alpha_i + \text{Month}_t + \text{Year}_t.
\end{aligned} \tag{6}
$$

Model Estimation and Results

Testing our hypotheses on the effect of customer participation variables on next box opt-in and spend involved estimating two vectors of the parameters, β_1 to β_8. To determine whether the hypothesized effects persist across boxes, we estimated decay parameters, λ_1 to λ_7 (as well as λ_8 for purchase ratio). Estimating decay parameters from the data, rather than simply assigning a decay value based on an assumed decay rate, requires a Bayesian approach. We used the Markov chain Monte Carlo (MCMC) Bayesian approach in Just Another Gibbs Sampler software to estimate the Type II Tobit model of box opt-in and box spend (Equations 1 and 2).[3] The estimation involved 40,000 MCMC iterations; we used 20,000 iterations as the burn-in period, and for the remaining 20,000 iterations, we used every fifth draw to reduce autocorrelations. The model estimation converged (the Geweke [1992] convergence z-score was within the ±1.96 interval, and all nodes passed the Heidelberger and Welch [1983] stationarity test, allowing us to make statistical inferences.

We present the posterior means of the estimated parameters for box opt-in and box spend models in Table 3. When describing the results, the β parameters refer to the short-term effects of customer participation with the previous box, and the λ parameters refer to the long-term effects of customer participation with the previous several boxes. Upcoming box participation has negative short-term ($\beta_{1,\text{opt-in}} = -.215$, $\beta_{1,\text{spend}} = -.183$) and long-term ($\lambda_{1,\text{opt-in}} = .582$; $\lambda_{1,\text{spend}} = .146$) effects on box opt-in and box spend, in support of H_{1a}. In contrast, delivered box participation has positive short-term ($\beta_{2,\text{opt-in}} = .068$, $\beta_{2,\text{spend}} = .017$) and long-term ($\lambda_{2,\text{opt-in}} = .146$, $\lambda_{2,\text{spend}} = .075$) effects on box opt-in and box spend, in support of H_{2a}. Finally, skipped box participation has negative short-term ($\beta_{3,\text{opt-in}} = -.049$, $\beta_{3,\text{spend}} = -.014$) and long-term ($\lambda_{3,\text{opt-in}} = .138$, $\lambda_{3,\text{spend}} = .219$) effects on box opt-in and box spend, in support of H_{3a}.

In terms of the way customers participated, delivered box emotionality has positive short-term ($\beta_{4,\text{opt-in}} = .081$, $\beta_{4,\text{spend}} = .019$) and long-term ($\lambda_{4,\text{opt-in}} = .507$, $\lambda_{4,\text{spend}} = .334$) effects on box opt-in and box spend, in support of H_{2b}. Similarly, delivered box concreteness has positive short-term ($\beta_{5,\text{ opt-in}} = .109$, $\beta_{5,\text{spend}} = .027$) and long-term ($\lambda_{5,\text{opt-in}} = .360$, $\lambda_{5,\text{spend}} = .120$) effects on both outcomes, providing support for H_{2c}. In contrast, skipped box emotionality has negative short-term ($\beta_{6,\text{opt-in}} = -.054$, $\beta_{6,\text{spend}} = -.006$) and long-term ($\lambda_{6,\text{opt-in}} = .323$, $\lambda_{6,\text{spend}} = .368$) effects on both outcomes, in support of H_{3b}. Similarly, skipped box concreteness has negative short-term ($\beta_{7,\text{opt-in}} = -.263$, $\beta_{7,\text{spend}} = -.085$) and long-term ($\lambda_{7,\text{opt-in}} = .092$, $\lambda_{7,\text{spend}} = .064$) effects on both outcomes, in support of H_{3c}. Further, when comparing the sizes of the λ coefficients for emotionality and concreteness, the coefficient is larger for delivered and skipped box emotionality for both box opt-in and box spend (i.e., in all four cases).

With regard to the control variables, we found that previewing the upcoming box in month t did not affect spending on that box, but suggesting changes to it did ($\theta_{3,\text{spend}} = .080$). Further, similar to the negative effect of upcoming box participation with box t−1 on the next box's purchases, suggesting changes to that box had a negative effect on the next box's spend ($\theta_{2,\text{spend}} = -.046$). For delivered boxes, providing more open-ended feedback increases box opt-in ($\theta_{4,\text{opt-in}} = .002$), whereas providing positive feedback increases both box outcomes ($\theta_{5,\text{opt-in}} = .056$, $\theta_{5,\text{spend}} = .268$). For skipped boxes, providing more open-ended feedback decreases spending on the next box ($\theta_{6,\text{spend}} = -.003$), but positive feedback increases both outcomes ($\theta_{7,\text{opt-in}} = .052$, $\theta_{7,\text{spend}} = .121$). Finally, higher purchase ratio has positive short-term ($\beta_{8,\text{opt-in}} =. 314$, $\beta_{8,\text{spend}} = .275$) and long-term ($\lambda_{8,\text{opt-in}} = .144$, $\lambda_{8,\text{spend}} = .023$) effects.

Discussion

Digitization has enabled companies to involve customers in multiple steps of the customer journey, and to do so repeatedly, all while capturing this journey with data. Box companies are particularly adept at this but still struggle with getting customers to treat the subscription box like an actual subscription and not an occasional purchase. What remained unclear was whether customer participation, in various forms, led to more box purchases. We considered this, as well as the possibility that customer participation can backfire, in both the short and long term. Overall, customer participation with the upcoming box, in terms of previewing its contents, lowered future box purchases. Further, all three of the participation variables that related to the skipped box—including whether to provide feedback and, if so, in emotional or concrete ways—decreased future box purchases. In contrast, all three of the participation variables that relate to the delivered box increased future box purchases. In summary, we found that customer participation before and after the delivered box appears to backfire, whereas participation with the delivered box drives future purchases. Further, the double-edged nature of customer participation has long-lasting effects (especially when feedback is conveyed with emotionality). We describe theoretical and practical implications of these findings and identify areas for future research based on the limitations of this research.

[3] We provide detailed descriptions of priors and the posterior conditional distribution in Web Appendix B.

Table 3. Joint Estimation Results of Box Opt-in and Box Spend.

	Box Opt-In Model$_t$		Box Spend Model$_t$	
	Posterior Mean	**Posterior SD**	**Posterior Mean**	**Posterior SD**
Short-Term Customer Participation				
Upcoming box participation$_{t-1}$ (H_{1a})	**−.215**	**.019**	**−.183**	**.012**
Delivered box participation$_{t-1}$ (H_{2a})	**.068**	**.018**	**.017**	**.005**
Skipped box participation$_{t-1}$ (H_{3a})	**−.049**	**.013**	**−.014**	**.006**
Delivered box emotionality$_{t-1}$ (H_{2b})	**.081**	**.021**	**.019**	**.003**
Delivered box concreteness$_{t-1}$ (H_{2c})	**.109**	**.024**	**.027**	**.006**
Skipped box emotionality$_{t-1}$ (H_{3b})	**−.054**	**.008**	**−.006**	**.001**
Skipped box concreteness$_{t-1}$ (H_{3c})	**−.263**	**.072**	**−.085**	**.012**
Long-Term Customer Participation[a]				
Stock upcoming box participation (H_{1a})	**.582**	**.228**	**.146**	**.044**
Stock delivered box participation (H_{2a})	**.146**	**.018**	**.075**	**.010**
Stock skipped box participation (H_{3a})	**.138**	**.027**	**.219**	**.017**
Stock delivered box emotionality (H_{2b})	**.507**	**.231**	**.334**	**.153**
Stock delivered box concreteness (H_{2c})	**.360**	**.046**	**.120**	**.051**
Stock skipped box emotionality (H_{3b})	**.323**	**.143**	**.368**	**.146**
Stock skipped box concreteness (H_{3c})	**.092**	**.038**	**.064**	**.021**
Control Variables				
Upcoming box participation$_t$	N.A.	N.A.	.013	.287
Upcoming box modification$_{t-1}$	.044	.030	**−.046**	**.010**
Upcoming box modification$_t$	N.A.	N.A.	**.080**	**.008**
Delivered box word count$_{t-1}$	**.002**	**.001**	.001	.001
Delivered box positivity$_{t-1}$	**.056**	**.007**	**.268**	**.065**
Skipped box word count$_{t-1}$	−.001	.008	**−.003**	**.001**
Skipped box positivity$_{t-1}$	**.052**	**.016**	**.121**	**.023**
Purchase ratio$_{t-1}$	**.314**	**.040**	**.275**	**.018**
Stock purchase ratio	**.144**	**.019**	**.023**	**.004**
Customer tenure$_t$	**−.173**	**.012**	**.019**	**.006**
Box retail value$_t$	N.A.	N.A.	**.237**	**.009**
New curator$_t$	−.134	.206	**−.327**	**.105**
Curator performance$_{t-1}$	.002	.011	.001	.001
Endogeneity correction terms				
Upcoming box participation copula	**.290**	**.015**	**.037**	**.004**
Delivered box participation copula	**−.183**	**.017**	**.030**	**.015**
Skipped box participation copula	**.124**	**.010**	**.022**	**.005**
Intercept	**.762**	**.281**	**3.036**	**.148**
Intercept heterogeneity	**.413**	**.122**	**1.977**	**.535**
Year and month fixed effects	Included		Included	

[a]For the long-term customer participation stock measures, estimates were bounded between 0 and 1; a higher value indicates that the effect is more persistent.
Notes: Boldface indicates that the 95% coverage interval does not span zero, resulting in statistically significant effects.

Theoretical Implications

We answer Palmatier et al.'s (2013) call for a more dynamic perspective of customer experience by integrating concepts from the marketing response-modeling literature (e.g., Schweidel and Knox 2013; Van Diepen, Donkers, and Franses 2009), such as customer memory, with concepts from the customer participation literature, such as touchpoint engagement (e.g., Blut, Heirati, and Schoefer 2020; Haumann et al. 2015). We differ from the marketing-response literature, however; specifically, rather than inferring the customer's "response" to the company's action using a firm-led measure, we directly measure the customer's response (participation). Further, we examine not only the dynamic impact of customer participation but also the dynamic impact of the way that customers participate, which the response-modeling literature has not done before.

We also capture customer dynamics across the customer journey. Although mapping the customer journey has become a priority (De Keyser et al. 2020; Lemon and Verhoef 2016), prior work has not tracked customer participation across stages to compare their effects. We achieved this and, in the process, found that the nature of the stages determines whether customer participation engages customers, which most of the literature expects, or disengages them, which is a novel finding.

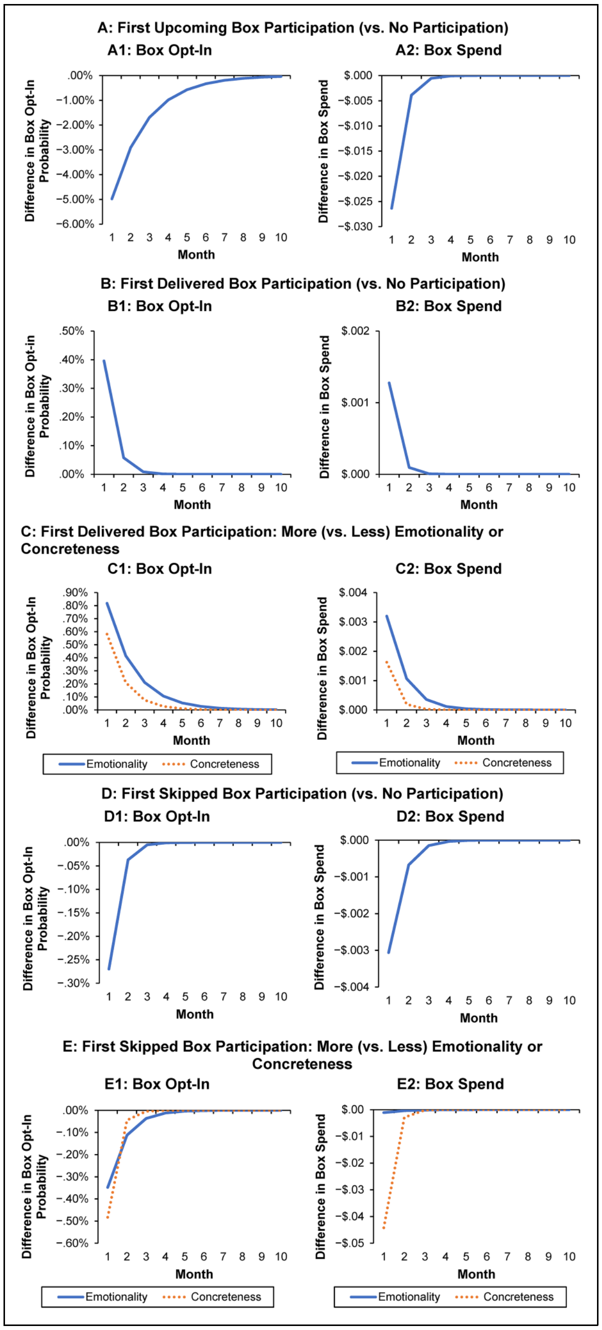

Figure 3. Impact of Optimal (vs. Suboptimal) Customer Participation with the First Box on Subsequent Box Purchases.

Prior work has provided important insights about managing customer participation to encourage its relational benefits (e.g., Blut, Heirati, and Schoefer 2020; Chan, Yim, and Lam 2010; Haumann et al. 2015), which have been tied to aggregate company performance (Auh et al. 2019). We add to this literature in three ways. First, we offer objective measures of customer participation and purchase behavior using secondary data, which complement prior work that used survey and hypothetical experiment-based measures. We propose new measures of customer participation. Customers' use of drop-down menus and open-ended text boxes, the latter of which can be mined to measure the way customers participate, are informative measures. Further, previewing behavior (relevant to other domains as well, such as virtual reality features that allow customers to "try on" products or AI-assisted configurators used to customize products) can be used to measure participation. Second, we are the first to measure the *way* customers participate and, by doing so, empirically illustrate concepts discussed in conceptual papers (e.g., De Keyser et al. 2020). Third, we show that *when* customers participate influences whether the very same type of participation benefits or harms customer–company relationships. Finally, we are one of the few, or potentially the first, to empirically link individual-level participation to individual-level purchase behavior.

In addition, an emerging area in marketing ties linguistic devices, such as emotionality (Rocklage, Rucker, and Nordgren 2018, 2021) and concreteness (Packard and Berger 2021), to consumer outcomes. This is accomplished by measuring how one person's linguistic choices have an impact on another person's behavior (e.g., the effect of emotionality in online reviews on customer behavior). Instead, we measure how one's own expression of emotionality or concreteness affects one's own behavior and, by doing so, steer the conversation about persuasion to one that includes self-persuasion. Further, by incorporating both attributes into a single framework, we are able to compare their effects. In general, the two produced similar results for delivered box participation (positive) and skipped box participation (negative). When consumers express emotionality or concreteness, it appears to signal the importance to them of that particular stage and, in return, solidify their role in engaging or disengaging with the company. Nevertheless, the two differ in some respects. Clarifying the ongoing debate about the relative longevity of affect versus cognition (e.g., Homburg, Koschate, and Hoyer 2006; Verhoef 2003), we find that concreteness has a larger immediate impact on purchases, whereas emotionality has a more enduring impact.

Managerial Implications

Drawing on our findings, we offer several recommendations to subscription box companies about when to encourage customer participation and ways of doing so. We achieved this in two ways. First, we plotted the long-term impact of a single instance of customer participation with the very first box on subsequent box purchases. For example, we plotted the difference between the impact of the customer's previewing the very first (upcoming) box versus the customer's choosing not to preview it (Figure 3).[4] Second, using insights gained from the plots, we

[4] For example, in Figure 3, Panel A1, we plot the long-term differences in box opt-in probability that result from two opposing previewing decisions with the very first box. The difference is calculated between the scenario in which the customer did not preview the very first box versus the scenario in which the customer did preview it. Because previewing decreases box opt-in, the difference is negative in month 1. Over time, however, the negative effect diminishes, and the difference becomes zero (there is no difference in opt-in probability). Still, a slower decline indicates a stronger long-term effect, whereas a sharp decline indicates a shorter long-term effect.

Table 4. Financial Impact of Redirected Customer Participation.

Customer Participation Touchpoint	Redirected Customer Participation	Percentage-Point Increase in Box Opt-In	Increase in Box Spend ($)	Average Increase in CLR
Upcoming box participation	Do not preview (decrease from 1 to 0)	5.61	$8.69	$276.95 (13.96%)
Delivered box participation	Provide feedback (increase from 0 to 1)	.51	$.29	$13.97 (.70%)
Delivered box emotionality	Increase feedback emotionality (increase from below average to average)	2.48	$1.09	$112.22 (5.66%)
Delivered box concreteness	Increase feedback concreteness (increase from below average to average)	2.44	$1.32	$112.76 (5.68%)
Skipped box participation	Do not provide feedback (decrease from 1 to 0)	.40	$.44	$8.98 (.45%)
Skipped box emotionality	Decrease feedback emotionality (Decrease to 10th percentile)	.57	$.24	$23.04 (1.16%)
Skipped box concreteness	Decrease feedback concreteness (Decrease to 10th percentile)	.76	$4.56	$195.49 (9.82%)

simulated redirecting participation for the 30,000 sample customers from suboptimal to optimal while accounting for dynamics and the effects of other variables included in the joint estimation results of box opt-in and box spend. Using the consequent projected changes in box opt-in probabilities and box spend, we calculated the CLR of optimally redirecting customer participation (Table 4).

Specifically, we calculated the box opt-in probability and spending in month t using customer participation (actual and redirected) in the previous month as a predictor while keeping the other variables constant using observed data. We then multiplied expected opt-in probability by expected spend to yield expected revenue for that month and applied this method recursively to the next 35 months (the use of a three-year time frame has been established in the literature; Datta, Foubert, and Van Heerde 2015; Kumar et al. 2008). We achieved a CLR value for both actual and redirected customer participation by adding the expected revenues for 36 months but with an annual discount rate of 8.5% (similar to prior work). The last column of Table 4 displays differential increases in CLR based on redirected customer participation.

Should box companies continue to encourage upcoming box participation? Based on the joint estimation results of box opt-in and box spend, upcoming box participation appears to hurt more than it helps. The customer's previewing just the first upcoming box lowers the probability of opt-in (Figure 3, Panel A1) and spend (Figure 3, Panel A2) for several subsequent boxes compared with the scenario in which the customer had not previewed the first box. We then considered entire estimation results, examining the financial impact of redirecting participation for the sample customers who previewed upcoming boxes. Had the customers not previewed the box (either by not explicitly being encouraged to do so or by not having the option to preview), this would have resulted in an increase of 5.61 percentage points in box opt-in and $8.69 in box spend, resulting in an increase of 13.96% or $276.95 in CLR (Table 4). This is the upside of discouraging box previewing that occurs despite the company's having to miss out on the positive impact of preview-based box modification on current box spend.

Should box companies continue to encourage more delivered box participation? The sample box company appears justified in encouraging customers to provide feedback about delivered boxes using drop-down menus and open-ended text boxes. This becomes evident when we look at the effect of participating (vs. not) with just the first delivered box on box outcomes for the next three boxes (Figure 3, Panels B1 and B2). Further, participating with 50% more emotionality or concreteness is associated with an immediate jump in box opt-in and box spend, and the effect of emotionality persists slightly longer (Figure 3, Panels C1 and C2). In terms of financial impact, redirecting the sample customers who did not participate with delivered boxes to participating with them would have increased box opt-in by .51 percentage points and box spend by $.29, resulting in a .70% or $13.97 gain in CLR. For the sample customers who participated with lower than average emotionality, redirecting them to participate with an average level of emotionality would have increased box opt-in by 2.48 percentage points and box spend by $1.09, yielding a 5.66% or $112.22 gain in CLR. For the sample customers who participated with low concreteness, had they been redirected to participate with average levels of concreteness, box opt-in would have increased by 2.44 percentage points and box spend by $1.32, yielding a 5.68% or $112.76 gain in CLR. Despite differences in trajectory, the overall financial benefits of increasing emotionality and concreteness are similar.

Should box companies continue to encourage skipped box participation? Box companies may think that, when customers skip a box, it is an ideal time to learn why they are disengaging. Nevertheless, there is some risk, as a customer's merely

Table 5. Strategic Recommendations for Box Companies.

Recommendation	Strategy	Potential Risk of Recommendation
Cautiously promote digital previewing for upcoming boxes.	Explicitly give customers the option to be surprised versus informed. Foster customers' curiosity to await the next box, for example, by crafting boxes that balance fit with revealed preferences and creative variability with new item suggestions. Provide unique and exclusive items or early releases. Enable previewing for some product categories but not others or rotate to maintain surprise/novelty elements.	Missing out on an opportunity to learn from customers. Because customers who preview and modify the box spend more on that box, limiting previewing will limit this benefit. However, the net effect of less previewing on box purchases is still positive after accounting for total effects of previewing and modification on current and future boxes.
Focus on the first box, not only from a product–taste match perspective but also from a customer participation perspective.	Focus less on co-opting customers before the first box arrives and more on co-opting them after the first box arrives. If customers choose to skip the second box, their chance of churning is high, so refrain from soliciting extensive box skip feedback. Rather, increase their interest in earning a new surprise.	Because early churn is a problem, box companies need to learn about customers' preferences, based on their feedback, including when they skip a box early on. Thus, our recommendation of limiting skipped box feedback prevents an opportunity to learn from customers.
Manage customer participation dynamics with the view that the good and the bad about participation are long-lasting.	In the short term, managing concreteness is relatively more important, whereas in the long term, managing emotionality is more important. The long-term negative effect of previewing is substantial, and, thus, it should be used sparingly. Course-correct if profitable customers with a high likelihood of churning engage in counterproductive participation.	Managing dynamics with different touchpoints for different customers adds complexity and potential costs.
Acknowledge the differential value of soliciting customer feedback across stages of the customer journey.	Engage customers and collect feedback with delivered box. Invite honest feedback, because even if it is less positive, emotional and concrete feedback pay off. Avoid excessive interactions with customers before the next box is shipped.	Customer fatigue.
Text-mine qualitative customer feedback.	Text-mine open-ended comments for sentiment, information, and linguistics. Capture word count, punctuation, and other metrics of text engagement. Establish a system for collecting and analyzing the data and leverage the data to improve operations and service.	Certain text engagement metrics can overwhelm the curator and make it difficult to know what to pay attention to when curating boxes. At the corporate level, data overload can cause managers to pay attention to certain metrics while ignoring other (more important) ones.
Solicit emotional and concrete feedback for delivered boxes, especially for the first box.	Ask customers about specific product attributes (concrete feedback) and how they feel about them (emotional feedback) and ask them to elaborate. Example questions include: "How did you feel about what you saw in the box?" (emotional) or "List the top three things that came to mind when you tried on this product." (concrete). Offer text-based symbols (e.g., emojis) and prepopulated options that are specific.	Customers' providing so much feedback is effortful and may dissuade certain customers.
Avoid having customers elaborate on why they are skipping a box.	Don't ask customers to provide extensive reasons why they are skipping a box. If anything, use close-ended questions rather than open-ended ones.	Potentially valuable feedback information and keeping in touch with the customer becomes discontinued.

providing skip feedback just once causes an immediate decline in box opt-in and box spend, which lasts for a few boxes (Figure 3, Panels D1 and D2). In terms of financial impact, redirecting participation for the sample customers who participated with skipped boxes by providing feedback to not participating would have increased box opt-in by .40 percentage points and box spend by $.44, resulting in a .45% or $8.98 gain in CLR. Further, participating with 50% more emotionality causes an immediate decline in box opt-in and box spend, and although the effect persists longer than when participating with concreteness, the immediate decline caused by concreteness is much steeper (Figure 3, Panels E1 and E2). In terms of financial impact, for the customers who participated with moderate to high emotionality, redirecting them to participate with low emotionality would have increased box opt-in by .57 percentage points and spend by $.24, resulting in a 1.16% or $23.04 gain in CLR. In comparison, lowering skipped boxed concreteness similarly would cause a .76 percentage-point increase in box opt-in and a $4.56 increase in spend, resulting in an overall increase in CLR of $195.49. Limiting concreteness is thus especially important. We present strategic recommendations on how box companies can limit concreteness here, and achieve financial gains outlined in the rest of this section, in Table 5.

Limitations and Directions for Future Research

We collected data from a single box company that focuses on apparel curation. The key findings should hold true for other types of subscription boxes as well, even if they do not allow returns but allow skipping (e.g., meal kits, personal hygiene or cosmetics boxes). Here, box opt-in becomes the focal outcome, making the findings about the negative effects of skipped box participation all the more important. Still, we recommend that future researchers consider testing the effects of customer participation in other "pseudo-subscription" settings, such as business formats that do not charge styling fees or box companies that merely deliver boxes "on demand" (but with a cocreation element) and offer their customers an opt-in option for regular deliveries. We captured the dynamics of box subscriptions in two ways. We explored the role of customer participation within a single box process (across customer journey stages) and across multiple box processes as a means to measure long-term effects. A third way to measure such dynamics would involve accounting for spillover effects from one participation touchpoint to another (Li and Kannan 2014). For example, one could measure the effect of upcoming box participation on delivered box participation, the effect of delivered box participation on skipped box participation, and so on. Although this approach was beyond the scope of our research and did not apply to our data (we failed to reject the null hypotheses using the Granger causality test), we urge others to consider incorporating this option if appropriate.

We established opposing effects of emotionality and concreteness on box purchases for delivered versus skipped boxes but were not able to do the same for the upcoming box. Box companies indeed allow customers not only to preview the upcoming box (and make changes) but also to provide feedback, which can be mined for emotionality and concreteness. Our partner box company, however, did not collect these data. We hope that others can test the proposition we offer ($P_{1b–c}$) if the data are available. Further, we did not test the underlying reasons for customer participation (including the way customers participate) as affecting box purchases in a certain way. We conjectured that it was due to the engaging and disengaging nature of the touchpoints, but the findings of this article can be bolstered using hypothetical experiments to provide process evidence. We encourage researchers and practitioners to test different participation strategies with different customer groups (e.g., new vs. tenured customers) using randomized field experiments. Because our partnering company serves primarily female customers, it would also be interesting to determine whether the role played by the surprise element of curated apparel boxes is moderated by gender differences (as has recently been posited by Kovacheva, Nikolova, and Lamberton 2022). Finally, we restricted our sample to customers who made at least two box purchases to measure customer participation with the first box and tie it to the next box's purchases. Given that many customers churn after the first box, however, future research could start from the beginning and examine why so many customers leave so quickly.

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