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Empirical investigation of digital strategies in online retail

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Empirical Investigation of Digital Strategies in Online Retail

by

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This dissertation examines digital strategies used by online retailers to engage customers and increase sales. The first essay investigates the impact of offering incentives to recapture lost sales from abandoned online shopping carts (i.e., customers adding items to their carts, but leaving without purchasing). Collaborating with an online fashion retailer, I conducted a randomized field experiment by manipulating the presence of incentives in recovery interventions. Findings reveal that incentives facilitate purchase conversion, but responsiveness to the incentives differs across various customer and cart characteristics.

In the second essay, I explore how retailers can leverage Augmented Reality (AR), a technology that helps users visualize how virtual objects fit into their physical reality, to enable customers to try products virtually. Using data from an international cosmetics retailer who incorporated AR in their mobile app, I find that customers who use AR display higher levels of in-app engagement, and are more inclined to explore products and brands they have never purchased before. Furthermore, AR benefits lower-priced products and less-popular brands and could potentially level the playing field for brands or products at the long tail of the product sales distribution.

The findings uncovered in these two essays contribute to the literature on digital marketing and retailing, and would benefit retailers who are planning to implement these strategies.

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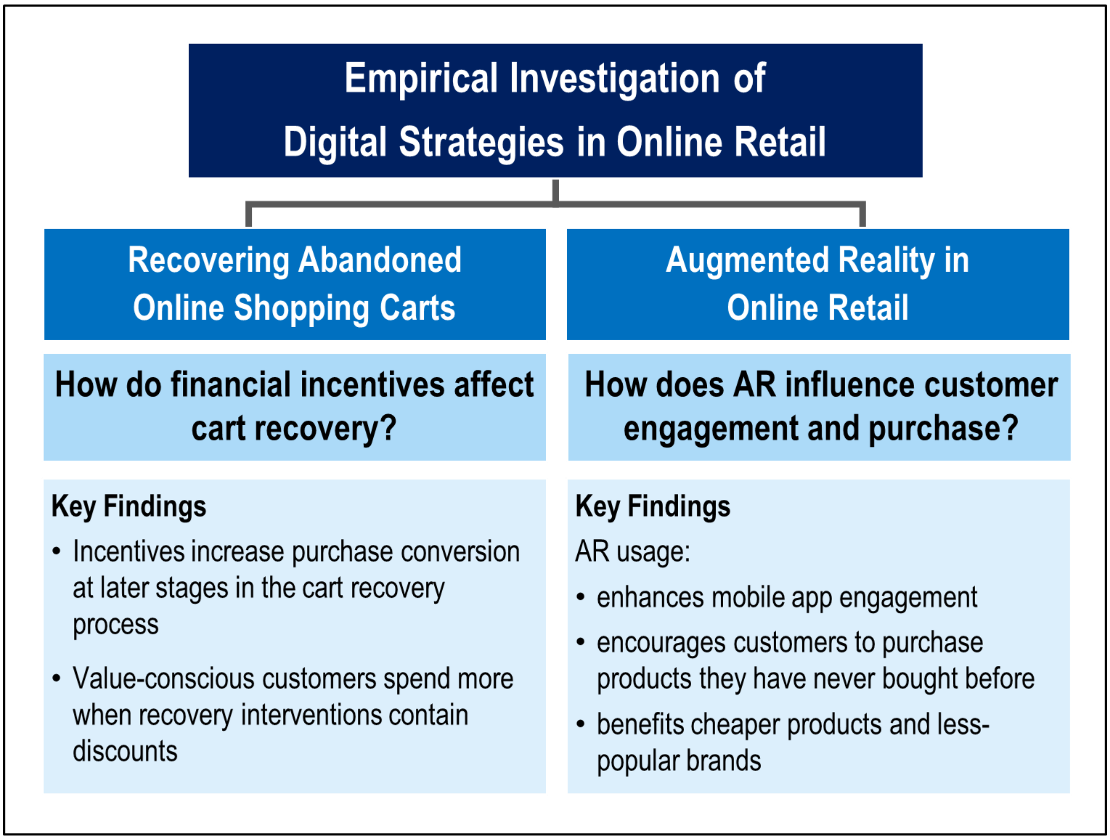
1. Dissertation Overview

The development of technology is changing the marketing landscape at a rapid pace. These emerging technological innovations present promising opportunities for retailers to engage customers and influence their behavior. This dissertation explores digital strategies that retailers can use to increase sales and gain a competitive advantage. Figure 1 provides an overview of the two essays in this dissertation.

Figure 1 Dissertation Overview



A challenge for online retailers is shopping cart abandonment (i.e., customers adding items to their carts, but leaving without purchasing). On average, 74% of online carts were abandoned in 2016 (Baymard Institute 2017). With the rise of mobile e-commerce, cart abandonment is poised to become an even bigger threat to online retailers (Business Insider 2016; Forbes 2013). While reasons for cart abandonment have been examined, strategies to recover carts post-abandonment have received less attention in the academic literature. As a result, there is still uncertainty surrounding the use of recovery interventions, with 1 in 2 marketing professionals expressing difficulty in implementing them (eMarketer 2017a).

Given the pervasive use of incentives to recover abandoned carts and paucity of extant research in this area, my first essay assesses the effectiveness and financial viability of offering incentives in online shopping cart recovery. To understand how characteristics of customers, cart composition, browsing sessions, and recovery interventions influence stages in the cart recovery process (i.e., revisits to the online retailer, conversion from revisits to purchases, and transaction value), I collaborated with an online retailer to conduct a field experiment by offering financial incentives to randomly selected customers after they abandoned their carts. Data for over 22,000 abandoned carts, with detailed information on customer browsing activity and transaction history were assembled and integrated at the customer-level.

Findings show that incentives facilitate purchase conversion among customers who revisit the online retailer, and increase total revenue from recovered transaction by 16.6%. In addition, responsiveness to incentives differs by customer and cart characteristics. For example, value-conscious customers purchase even more when they are offered a discount, while coupon-prone customers who opened emails that did not contain discounts were even less likely to purchase compared to those who did not open emails. Additionally, I also assessed the minimum gross margin required to ensure the financial viability of offering discounts to help retailers determine when they should use incentives to recover abandoned carts.

My second essay examines how Augmented Reality (AR) can be used to increase sales in online retail. AR is an emerging technology that integrates digital elements onto a live view of the physical environment, creating alternate perceptions of reality. By retaining real-world environments as a backdrop, AR helps users to visualize how these digital elements fit into their physical reality. Thus, a promising application of this technology in retail is letting customers experience products virtually before making a purchase, especially in online contexts where customers have no access to physical products. While firms are keen to invest in AR, research documenting customers' responses to AR in real-world context is limited. Even though more than 40% of executives from leading global brands plan to make significant investments in AR/VR (KPMG 2017), close to 30% of marketing managers identified AR/VR as the technology they are most unprepared for (eMarketer 2017b).

To provide a better understanding of how retailers can leverage this emerging technology to improve customer engagement and increase purchase, I obtained data from an international cosmetics retailer who incorporated AR in their mobile app, enabling customers to try cosmetic products (lips and eyes products, e.g., lipsticks, eyeliners) virtually. Introduction time for the AR feature was staggered by product categories, allowing me to account for self-selection bias arising from customers' decision to use the feature. The dataset contains more than 1.5 million observations for over 2,800 products and 63,000 customers, enabling me to examine how AR's influence differs across product and customer characteristics.

To summarize, I find that customers who use AR on the mobile app spend 52.6% more time and view 3.3 times more products on average. Additionally, session purchase rate is 14.7% higher when customers use AR, with the increase coming mainly from customers who have made previous online purchases with the retailer. At the product level, AR benefits lower-priced products and less-popular brands with lower share of sales, suggesting that price and brand popularity become less important as extrinsic quality cues when customers are able to try products virtually. Furthermore, AR is particularly effective at encouraging customers to explore products and brands they have never purchased before.

I conclude both essays by discussing potential implications of findings from the research. With these two essays, I hope to provide relevant and current insights that are actionable for marketing managers in a digital age, and contribute meaningfully to the existing literature on digital marketing and retailing.

2. Recovering Abandoned Online Shopping Carts

2.1 Introduction

Online retail has been growing at a staggering rate in recent years – consumers worldwide made $2.3 trillion worth of purchases online in 2017, and this figure is expected to exceed $4 trillion by 2020 (eMarketer 2017c). A pervasive challenge in online retail is shopping cart abandonment (i.e., customers adding items to their carts, but leaving without purchasing). On average, 74% of online carts were abandoned in 2016 (Baymard Institute 2017). With the rise of mobile e-commerce, cart abandonment is poised to become an even bigger threat to online retailers (Business Insider 2016; Forbes 2013).

Fortunately, up to 60% of these abandoned carts are potentially recoverable (Business Insider 2016). Thus, retailers are increasingly using interventions to salvage abandoned carts. According to eMarketer (2017d), 76% of marketing professionals have either implemented email recovery interventions, or are planning to implement them. Nevertheless, while reasons for cart abandonment have been examined (e.g., Kukar-Kinney and Close 2010; Rajamma, Paswan and Hossain 2009), research on strategies to recover abandoned carts is sparse. Industry research exploring customers' acceptance of recovery interventions (e.g., Marketing Sherpa 2015; VWO 2016) or outlining existing interventions used by retailers (e.g., number of emails sent, time of emails; Bronto 2012; Listrak 2015) provide little guidance because they do not assess actual effectiveness of these interventions. As a result, there is still uncertainty surrounding the use of recovery interventions, with 1 in 2 marketing professionals expressing difficulty in implementing them (eMarketer 2017a). Furthermore, even though 3 in 4 retailers offer monetary incentives in recovery interventions (e.g., discounts, Listrak 2015), the role of incentives in cart recovery is still unclear. Since the use of monetary incentives directly impacts retailers' bottom line, a deeper understanding of its efficacy in cart recovery is of great interest and importance.

Given the pervasive use of incentives to recover abandoned carts and paucity of extant research in this area, the present research focuses on the role of incentives in cart recovery to help marketing managers utilize incentives effectively and efficiently. I consider stages in the cart recovery process (i.e., revisits to the online retailer, conversion to purchase, and post-purchase product returns) to address the following research questions:

1. How do incentives affect customers' progression along stages in the cart recovery process?
2. How do incentives moderate the influence of customer and cart characteristics in the recovery process?
3. What is the minimum gross margin (before discount) required for incentives to be a viable financial option?

I investigate these research questions by collaborating with a leading online fashion retailer in Asia-Pacific to conduct a field experiment involving the retailer's most profitable customers. Across a period of 4 months, customers who abandoned their online shopping carts received an email intervention from the retailer, half of which contained a 15% discount voucher code, while the other half did not contain any voucher code. Random assignment was used to rule out any selection effects in order to establish a clear causal relationship between incentives and cart recovery. Detailed records of transaction history, browsing characteristics during the abandoned session, and interactions with email interventions were collected for each customer. This granular data provides a unique opportunity to understand the cart recovery mechanism at a disaggregate level. To disentangle the effects of incentives along stages of the recovery process, I estimated four models i.e., revisits to the online retailer, conversions from revisit to purchase, value of recovered transactions, and post-purchase product returns.

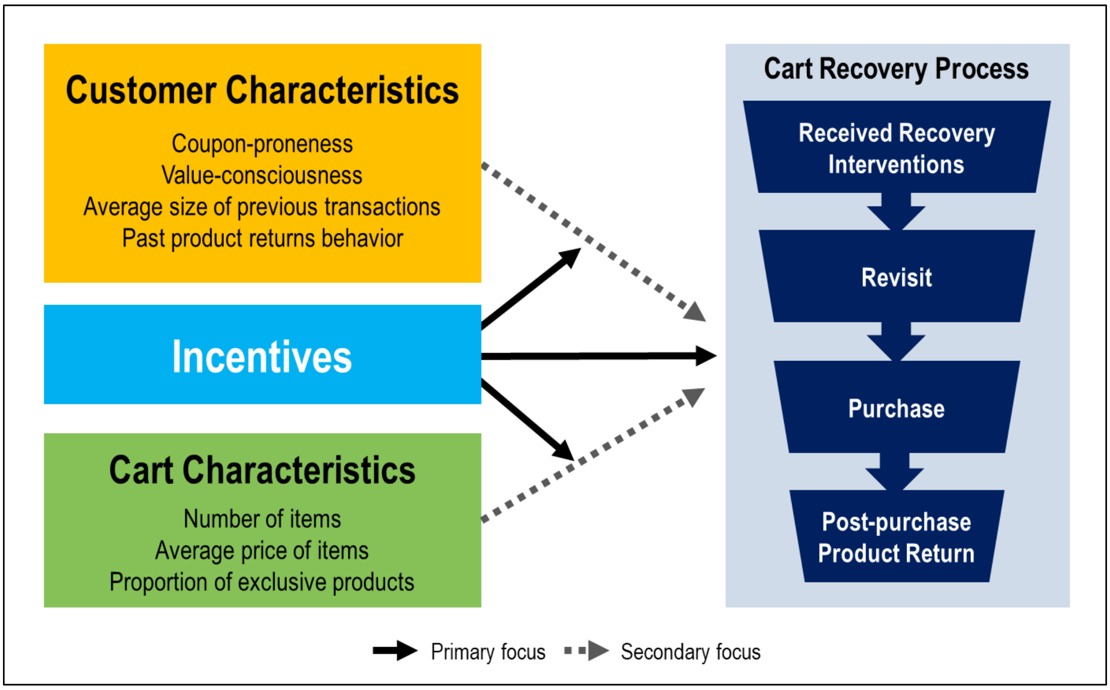
I find that incentives increase the likelihood of purchase among customers who revisit the retailer. Among customers who opened the email interventions (note: incentives were only visible when customers open the email), total revenue from recovered transaction increased by 16.6% when incentives were offered. While coupon-prone customers are less likely to purchase if they open email interventions that do not contain incentives, value-conscious customers and customers with larger transaction size (based on previous transactions) purchase even more when they are given a discount. I also find that customers with a high proportion of product returns in previous transactions are more responsive to recovery interventions, but they have a higher likelihood of returning products from the recovered transaction. Similarly, the likelihood of post-purchase product returns increases as the proportion of exclusive products in the recovered transaction increase. Furthermore, customers who revisit on mobile devices after receiving recovery interventions are less likely to purchase, and transactions recovered from mobile devices have lower value compared to those that are recovered on desktops. Finally, I find that for a 15% discount to be justified, the retailer should have a profit margin of at least 56.5% before offering the discount. Insights from this study would provide guidance for retailers to ascertain if recovery interventions and incentives are appropriate to achieve their business objectives (i.e., increase revisits, conversions, or value recovered).

From a theoretical perspective, the present research contributes to the online retailing literature by isolating the role of incentives as an instrument for improving conversion in the cart recovery process. In addition, I document the moderating influence of incentives on the effects of various customer and cart characteristics along the recovery process. Consistent with prior work on coupon-proneness and value-consciousness (Lichtenstein, Netemeyer, and Burton 1990; Pillai and Kumar 2012), my findings also provide empirical evidence of their diverging effects and extends discussion on the distinction between these two customer characteristics.

2.2 Research Framework

To provide a nuanced understanding of the role of incentives in cart recovery, I consider how incentives alter customers' response to recovery interventions along the recovery process. In addition, I also explore how incentives moderate the influence of various customer and cart characteristics in the process. Figure 2.1 below presents an overview of the research framework.

Figure 2.1 Research Framework



Before elaborating on different stages in the cart recovery process, a brief review of cart abandonment is provided.

2.2.1 Cart Abandonment

Online cart abandonment occurs when customers add items to their virtual shopping carts, but end the online session (by exiting the website, or due to prolonged period of inactivity) before completing the purchase (Kukar-Kinney and Close 2010). Extant research elucidates some causes of the phenomena, such as, encountering inconveniences like mandatory account creation or technical glitches (Rajamma, Paswan and Hossain 2009), heightened risk perceptions associated with online transactions (Moore and Mathews 2006; Schlosser, White and Lloyd 2006), usage of online carts as an organization or research tool e.g. adding items into carts to obtain total cost for price comparison (Kukar-Kinney and Close 2010; Negra and Mzoughi 2012; Xu and Huang 2015).

While reasons for cart abandonment have been examined and modifications to the online shopping process have been suggested to reduce cart abandonment before they occur (e.g., Bronto 2012; Schlosser, White and Lloyd 2006; VWO 2016), strategies to recover carts post-abandonment have received less attention in the academic literature. Adding items to cart is an expression of customers' interest and consideration in the products, and recovering these transactions may be less costly for retailers than acquiring new customers. Given that up to 60% of abandoned carts are potentially recoverable (Business Insider 2016), it is important to understand how recovery interventions can be used to effectively recapture lost sales. In the following section, I decompose the recovery process into distinct stages to better expound on the cart recovery mechanism.

2.2.2 Cart Recovery Process

In an online environment, the cart recovery process is sequential; although customers may drop out at any stage, they must progress through a series of consecutive stages to complete a transaction.

Receiving recovery interventions. The recovery process is initiated when customers receive interventions from the retailer after abandoning their carts. While customers may return to the retailer in the absence of any interventions, I do not consider these cases as part of the retailer-initiated recovery process because these customers returned on their own accord. Recovery interventions act as simple reminders to increase salience of abandoned cart items, but they may also communicate additional information (Lovett and Staelin 2016; Moriguchi, Xiong and Luo 2016) or contain special incentives (e.g., discounts, free gifts or free shipping, Listrak 2015) to entice customers to complete the transaction.

Revisit. Upon receiving the recovery interventions, customers can disregard the interventions, or respond by revisiting the online retailer through the retailer's website or mobile app. If customers do not revisit the retailer, the recovery attempt is not successful and the transaction is lost. However, if customers revisit the retailer, the interventions are deemed to have an impact in advancing customers further down the recovery process.

Purchase. During the revisit to the online retailer, customers retrieve items that were previously left behind in the cart. They may modify contents in the cart by removing previously added items or adding new items. Subsequently, customers would decide if they want to purchase items in the cart, or leave the online retailer without making a purchase. If they leave without making a purchase, the interventions are not effective in recovering the previously abandoned cart. However, if customers make payments and complete the transactions, the interventions are successful in recovering the abandoned carts.

Post-purchase product returns. For most online retailers, the transaction does not end when the purchase is made. Research has shown that at least 30% of products purchased online are returned (compared to about 10% from brick and mortar stores, Wall Street Journal 2013). This rate may be even higher if retailers have lenient product returns policies that encourage product return behavior. For example, some retailers accept product returns up to 30 days after products are received, and even offer free shipping for products that are returned. Customers may take advantage of lenient product returns policies by purchasing additional products to qualify for certain benefits (e.g., a discount or free shipping) with the intention of returning these products subsequently. If most of the purchases salvaged by recovery interventions are eventually returned to the retailer, effectiveness of the interventions may be inflated. Hence, I extend the recovery process to include a post-purchase product returns stage in the research framework.

The revisit and purchase stages in the proposed cart recovery process reflects existing research documenting purchase funnels in an online environment (e.g., Hu, Du and Damangir 2014; Li and Kannan 2014; Wiesel, Pauwel and Arts 2011). I distinguish my work from extant literature by examining the purchase funnel in the modified context of recovering abandoned carts, and extending the funnel to incorporate post-purchase product returns.

2.2.3 Incentives in Cart Recovery

According to Listrak (2015), 3 in 4 online retailers offer monetary incentives to recover abandoned carts. While these incentives may not alleviate all concerns that induce cart abandonment, they may serve as additional motivation for customers to complete the transaction. Understanding the effectiveness of monetary incentives in cart recovery is important because it directly impacts retailers' bottom line, but research has not examined when and how incentives should be used to recover abandoned carts. If the improvement in recovery rates is marginal with the use of incentives (i.e., customers would purchase anyway without incentives), offering incentives would reduce profits for the retailer. Hence, it is worth investigating if the use of incentives augment or attenuate customers' responsiveness to recovery interventions.

To examine the role of incentives in cart recovery, we can assess its effectiveness in moving customers along stages in the recovery process, from encouraging revisits post-abandonment (i.e., Revisits), to converting these revisits into purchases (i.e., Conversions). It is also important to consider the value of transactions recovered (i.e., Value Recovered) to evaluate incremental contribution to revenues. Knowledge of the role of incentives in the recovery process would help retailers determine if incentives are an appropriate tool to achieve their business objectives (i.e., increase revisits, conversions, or value recovered). This approach most closely reflects Lam et al.'s (2001) decomposition of sales response into attraction (i.e., consumers' store entry decision), conversion (i.e., consumers' decision to purchase at the store upon visiting), and spending effects (i.e., value of the transaction). In addition, given the prevalence and financial implications of product returns (Han, Chandukala and Che 2017), I also consider the impact of incentives on post-purchase product returns (i.e., Product Returns).

For the purpose of this paper, I focus on percentage discounts; the research can be extended to other forms of monetary incentives in future studies. I expect incentives to improve recovery rates by encouraging revisits to the retailer and conversions to purchase. However, transactions recovered using incentives would have lower value, as a portion of the recovered value would be negated by the discount. Furthermore, the impact of incentives on product returns is ambiguous. On one hand, incentives may encourage impulse purchases, leading to higher product returns for recovered transactions. On the other hand, items purchased with incentives may have lower perceived value and consequently, are less likely to be returned (Petersen and Kumar 2009).

2.2.4 Moderating Influence on Customer and Cart Characteristics

Furthermore, I also explore the moderating influence of incentives on various customer and cart characteristics, as these variables are commonly used by retailers to target incentives in their cart recovery efforts. By incorporating these characteristics into the framework and analyses, findings from this research will be more managerially relevant and actionable.

Coupon-proneness. Coupon-proneness refers to customers' propensity to use coupons arising from the psychological satisfaction of taking advantage of a good deal (Lichtenstein, Netemeyer and Burton 1990). Hence, I expect coupon-prone customers to be more sensitive to incentives in the revisit and conversion stages of the recovery process. As coupon-prone customers mainly focus on the act of redeeming coupons rather than the value of items purchased (Lichtenstein, Netemeyer and Burton 1990), I do not expect incentives to influence the relationship between coupon-proneness and value of recovered transactions. Furthermore, due to their desire to take advantage of incentives, coupon-prone customers have a higher likelihood of engaging in impulse purchases of products that they may not need

(Lichtenstein, Netemeyer and Burton 1990). These customers may be more likely to experience post-purchase regret, leading to higher product returns. Thus, I expect incentives to increase post-purchase product returns among coupon-prone customers.

Value-consciousness. Past research has distinguished between value-consciousness and coupon-proneness (Lichtenstein, Netemeyer and Burton 1990; Pillai and Kumar 2012). Value-consciousness is defined as the "concern for paying low prices, subject to some quality constraint" (Lichtenstein, Netemeyer and Burton 1990). The key distinction between value-consciousness and coupon-proneness customers is that the latter primarily derives pleasure from taking advantage of a deal rather than the gratification from consuming the purchased product. As monetary incentives indirectly enhance the acquisition utility of products by reducing price, I expect value-conscious customers[1] to respond positively to incentives in the revisit and conversion stages, albeit to a lesser degree compared to coupon-prone customers. In contrast to coupon-prone customers however, I expect value-conscious customers to purchase more when a percentage discount is offered, since a discount would increase the quality-to-price ratio of all items. In addition, as value-conscious customers are fundamentally interested in the need-satisfying properties of products (Lichtenstein, Netemeyer and Burton 1990), they would be less inclined to engage in impulse purchases regardless of the presence of incentives. Hence, I do not expect incentives to moderate the relationship between value-consciousness and product returns.

Average size of previous transactions. When a percentage discount is offered, customers with higher average transaction size would be able to enjoy more

[1] For exposition purposes, I use the terms "coupon-prone customers" and "value-conscious customers". However, coupon-proneness and value-consciousness are distinct characteristics, and they do not lie on two ends of the same continuum – customers can be both coupon-prone and value-conscious.

substantial savings (in absolute terms). Thus, I expect customers with higher average transaction size to be more responsive to incentives in the revisit and conversion stage. In addition, I expect the value of recovered transactions from these customers to increase when incentives are offered.

Product return behavior. By lowering the cost of products, monetary incentives reduce the risk of purchase. However, extant research has proposed the risk mitigation function of product returns (Petersen and Kumar 2015), and customers demonstrating recurrent product returns behavior (Shah, Kumar, and Kim 2014) may experience less risk. Thus, these customers may be less sensitive to the reduction in risk offered by incentives. Consequently, I expect customers with high proportion of product returns to be less responsive to incentives in the revisit and conversion stages. Additionally, as previously discussed, discounts may lower the likelihood of product returns by diminishing perceived value (Petersen and Kumar 2009). I expect this reduction in product returns to be more pronounced among customers with a higher propensity of returning products.

Average price of cart items. As the average price of items in the cart increase, there is a higher likelihood that the cart was abandoned due to price-related concerns. Thus, incentives should bolster revisits and conversions when the average price of items in customers' abandoned carts are high. In general, the average price of items in abandoned carts should be positively related to the value of recovered transactions. However, when percentage discounts are offered, the loss in potential revenues (due to discounts) increases with the average price of items in the cart. Thus, in the presence of discounts, I expect the relationship between average price of items and value of recovered transactions to be weakened.

Number of cart items. Most online retailers provide an option for customers to keep a separate record of items they do not intend to purchase immediately (e.g., “List” in Amazon, Best Buy, and Walmart). Hence, I consider the addition of items to cart as an explicit indication of customers’ purchase intention in the product, and not merely a concomitant action in the browsing process (e.g., formation of consideration sets). As the number of cart items increase, incentives become more appealing to customers because they would be able to apply the discount to purchase more items under consideration. Hence, I expect revisits and conversions to improve among customers with more items in their abandoned carts when incentives are offered. Controlling for the average price of cart items, I do not expect incentives to alter the relationship between number of cart items and the value of recovered transactions or post-purchase product returns.

Proportion of exclusive products. Some online retailers carry products that are sold exclusively on their websites, and these products cannot be obtained through other online or offline channels (e.g., private labels). For example, in addition to their own private label, international fashion retailer ASOS occasionally collaborates with other brands to carry exclusive products that are not available elsewhere. Due to the absence of alternatives, customers are unable to engage in price-comparison shopping. Thus, demand for exclusive products may be more price-inelastic than non-exclusive products. Consequently, incentives should have a weaker impact among customers with a higher proportion of exclusive products in their abandoned carts. As a corollary, incentives should improve revisits and conversions among customers with lower proportion of exclusive products. Controlling for average price of items, I do not expect the proportion of exclusive products to influence recovered transaction value and post-purchase product returns.

In summary, my proposed framework outlines stages in the recovery process and offers some measures to assess effectiveness of incentives along this process (i.e., revisits to the retailer, conversion to purchase, value of recovered transactions, and post-purchase product returns). In addition, I suggest some moderating effects of incentives on various customer and cart characteristics along the recovery process. Finally, I conduct profit margin analysis to aid retail managers understand the feasibility of implementing an incentive based approach for cart recovery.

2.3 Methodology

2.3.1 Field Experiment

To investigate the research questions, I collaborated with a leading online fashion retailer in Asia-Pacific to conduct a field experiment. The retailer is part of the world's leading online fashion group for emerging markets, and has presence in seven countries. The retailer carries items from various categories, including clothing, shoes, and accessories for men, women, and kids. In addition to the retailer's private-label products, over a thousand local and international brands are offered. The retailer offers free delivery when the transaction value exceeds a certain amount. If transaction value is below the threshold, the retailer charges a flat shipping fee between $1 and $2.50 depending on location, but independent of the weight of the purchased items. As shipping costs are marginal, it is unlikely that carts were abandoned due to high unexpected costs. Besides that, the retailer also has a 30-days free returns and exchange policy. Customers can purchase via the retailer's online website or mobile application. On these platforms, items are displayed with an image, brand and product name, original price, discounted price, and discount percentage. The platforms also have a wish-list function to allow customers to keep a separate record of items they are interested in, but do not intend to purchase immediately. Thus, I am able to isolate cart abandonment from other decision-making processes (e.g., formation of consideration sets). Customers have to create an account with a unique email address or sign in via Facebook to make a purchase. This identification at the user level enables me to track cart activity, transaction history, and marketing communications received for each customer.

To control for unobserved heterogeneity among customers, I worked with the retailer to identify a group of customers with similar characteristics. The retailer focused on customers with the top 10% total transaction value in their cohort (i.e., grouped by the month of their first transaction) in one of the retailer's bigger markets, as these are the most active and profitable customers. Furthermore, as these customers have purchased from the retailer before, it is unlikely that their carts were abandoned due to transaction inconvenience (e.g., account creation) or privacy and security concerns. Focusing on a subset of similar customers helps to rule out alternate explanations and ensures a clean study and field experiment.

Across a 4-month period (April 2017 to July 2017), the retailer sent more than 22,000 recovery interventions to these customers after they abandoned their online shopping carts (i.e., if no purchase was made within 24 hours after items were added into the cart). Half of the interventions contained a 15% discount, and the other half were identical aside from the discount (i.e., no discount). These interventions were randomized, and each customer had a 50% probability of receiving a discount after abandoning the cart. The discount was included in the body of the email, and was only visible if customers opened the email. In addition, customers in the field experiment did not receive any other recovery interventions in the seven days following the cart abandonment, allowing me to clearly attribute success of cart recovery to the experimental manipulation. Details of the randomization checks are provided in the next section.

After the field experiment concluded, I assembled a dataset containing the following information:

- *Cart activity*: exact time each item was added or removed from the cart by the customer, item details, and device used during the browsing session.
- *Email history*: full history of emails received by the customer, including the type of emails, the exact time they were received, opened, and clicked.
- *Transaction history*: full history of purchases and product returns made by the customer, including item details, discount applied, and device used for the transactions.

By matching these records at the user-level, I am able to measure customers' responses to the recovery interventions at a disaggregate level.

2.3.2 Descriptive Evidence

During the 4-month period of the study, close to \$4.4 million worth of items were abandoned by the retailers' top customers, translating to \$13.2 million annually in the focal market. The value of transactions recovered after accounting for product returns is close to \$330,000 over the period of the experiment, representing \$1 million annually.

The proportion of customers who received incentives and customers who did not receive incentives were roughly equal (49.5% with incentives vs 50.5% without incentives). To ensure that randomization was done properly and those who received incentives are similar to those who did not, I compared the transaction and browsing histories of these two groups of customers. This result, reported in Table 2.1, confirmed that the two groups are statistically similar ($p > .25$ for all variables).

Table 2.1 Comparison of Pre-Treatment Differences among Experimental Groups

	Mean of group with discount	Mean of group without discount	p-value
Weeks from last order	8.191	8.141	0.747
Weeks from first order	52.139	52.158	0.948
Number of previous orders	10.139	10.255	0.434
Number of orders per month	1.213	1.230	0.493
Average value per order ($)	57.507	57.865	0.561
Duration of Abandoned Session (minutes)	12.941	12.860	0.679
Past 2 weeks browsing duration (minutes)	53.432	54.883	0.264

In addition, based on the setup of the field experiment, customers would only be aware of the discounts after opening the email interventions. Thus, email open rates should be similar in both conditions. Comparison of the open rates for both conditions further validated that the randomization was done correctly - the open rates of emails with and without incentives were not significantly different (21.1% with incentives vs 20.6% without incentive, $p = .331$). Furthermore, customers who opened emails with discounts were more likely to click on the link in the email (6.0% with incentives vs 4.0% without incentives, $p < .01$), suggesting that the manipulation was effective, and customers in the incentive condition noticed the discount voucher code.

As previous research has found that differences between customers who open emails versus those who do not (Kumar, Zhang and Luo 2014), my analyses focus on comparing three segments of customers: customers who did not open the emails, customers who opened emails which did not contain a discount, and customers who opened emails which contain a discount. Comparison of the first two segments captures the difference between customers who open emails and customers who do not open emails. Of greater interest, differences between the latter two segments represent the incremental effects of offering incentives to customers. Summary statistics for the total sample and these three segments are presented in Table 2.2.

Table 2.2 Descriptive Evidence

	(1) Total Sample	(2) Did Not Open Email	(3) Opened Email; No Discount	(4) Opened Email; With Discount
Overall Recovery Rate	26.93%	24.75%	33.36%***	37.05%***
• **Revisit Rate**	66.34%	64.43%	72.87%***	74.26%
• **Conversion Rate**	40.60%	38.42%	45.78%***	49.88%**
Mean Value Recovered before accounting for Product Returns (among recovered transactions)	$71.17	$70.75	$71.53	$72.99
Product Return Rate (among recovered transactions)	31.94%	30.87%	35.56%**	34.15%
Mean Value Recovered after accounting for Product Returns (among recovered transactions)	$55.29	$55.60	$53.26	$55.55
Sample Size	22,058	17,457	2,293	2,308
** p ≤ .10; ** p ≤ .05; *** p ≤ .01*			*Note: tested against Column (2) for significance*	*Note: tested against Column (3) for significance*

The Overall Recovery Rate is given by the proportion of transactions recovered within seven days after receiving email interventions. I chose a seven-day window to assess effectiveness of the interventions since no other recovery interventions were sent by the retailer during this seven-day window period. In addition, the seven-day window is used by the focal retailer to attribute conversion, and is also widely used in the industry (e.g., Facebook 2016; Google 2016). In total, the retailer was able to recover more than 1 in 4 carts within seven days from abandonment.

To disentangle effectiveness of the interventions along different stages of the recovery process, I split the Overall Recovery Rate into the Revisit Rate (given by the proportion of customers who revisited the retailer after receiving the intervention) and Conversion Rate (given by the proportion of customers who made a purchase after revisiting the retailer). Thus, unlike Overall Recovery Rate, Conversion Rate represents movement from the revisit to purchase stage, and is conditional on customers revisiting the retailer. Value Recovered refers to the value of all items purchased from the recovered transaction, after accounting for any discounts, before including shipping cost.

Comparison of Column (2) with Column (3) in Table 2.2 suggests that customers who open email interventions are more likely to revisit the retailer, and they are also more likely to purchase upon revisiting the retailer. However, these customers have a higher probability of returning products post-purchase compared to customers who do not open email interventions. More importantly, among customers who open email interventions (i.e., comparison of Column (3) and Column (4)), the presence of incentives does not have an incremental effect on revisits, but increases the probability of purchase (conversions) among customers who revisit the retailer. After accounting for product returns, the total value of recovered transaction among customers who opened emails containing discounts was $47,500 (vs $40,700 among customers who opened emails that did not contain discounts), representing a 16.6%

increase in revenue. Thus, even with a 15% discount, the revenue from recovered transaction is still substantially greater when incentives are offered.

While the descriptive statistics provide a cursory view of the effectiveness of incentives across stages in the recovery process, they do not elucidate how incentives moderate the influence of customer and cart characteristics in cart recovery. In addition, they do not account for potentially confounding variables, such as the time the interventions were received, as well as other customer, cart, and browsing characteristics. To augment the descriptive evidence, I developed four models to represent Revisits to the retailer, Conversion from revisit to purchase, Value Recovered, and post-purchase Product Returns.

2.4 Empirical Model

In all four models (i.e., Revisit, Conversion, Value Recovered, Product Returns), the unit of analysis is the email interventions received by customers after they abandoned their carts. I used the same explanatory variables in these models to facilitate comparison across the models.

To account for the right-censored nature of Revisits, I used a proportional hazard regression (Cox 1972), with time to revisit after receiving intervention, $t^{Revisit}$, as the dependent variable. This approach is consistent with previous work on purchasing behaviour in online environments (Lambrecht and Tucker 2013, Manchanda et al. 2006). By considering the rate of event occurrence (i.e., hazard rate), the proportional hazard regression differs from the logistics regression, which considers the proportion of event occurrence within a predetermined timeframe (i.e., odds ratio). The hazard rate at time ‘t’ is made up of two components – the baseline hazard function, $h_0(t)$, which represents the change in probability of event occurrence per unit time given that the event has not occurred, and a function of covariates measuring the effect of predictors on the hazard function. The baseline hazard function captures the underlying probability of event occurrence when all the covariates are equal to zero, and is analogous to an intercept term in a typical regression model. As no assumptions of the nature of the baseline hazard function is required, the proportional hazard model is semi-parametric. The expected hazard function for Revisit for subject 'i', conditional on a set of covariates X, can be expressed as

$$(1)\ \mathrm{h}\left(t^{Revisit}|X_i, \beta^r\right) = h_0\left(t^{Revisit}\right) \times \exp(X_i\beta^r)$$

Equation (1) can be rewritten in the following form:

$$(2)\ \frac{h(\mathrm{t}^{Revisit})}{\mathrm{h}_0(\mathrm{t}^{Revisit})} = \exp(X_i\beta^r)$$

Thus, the proportional hazard model measures the multiplicative effects of the vector of covariates X on the hazard function relative to the baseline hazard function, and the exponentiated coefficients gives the impact of each covariate on the hazard ratio.

The Conversion model is similar to the Revisit model with two key differences. First, the sample comprised of email interventions that led to revisits by customers who have previously abandoned their carts. Second, time to purchase after receiving intervention, $t^{Conversion}$, is used as the dependent variable. The hazard model for Conversion, conditional on a set of covariates X, is expressed as

$$(3)\ \frac{h(\mathrm{t}^{Conversion})}{\mathrm{h}_0(\mathrm{t}^{Conversion})} = \exp(X_i\beta^c)$$

For the Value Recovered and Product Returns models, the sample consist of email interventions that successfully recovered abandoned carts. Value Recovered represents the value of the transaction recovered by the email, and was calculated as the sum of price paid for all items in the cart, after accounting for item-level and order-level discounts, before deducting the value of items that were subsequently returned. The regression model for Value Recovered by email 'i' is represented by

$$(4)\ \text{ValueRecovered}_i = X_i\beta^v + \varepsilon_i$$

For Product Returns, I use a logit specification, with 1 indicating that the customer returned at least 1 item from the transaction recovered by the email intervention, and 0 indicating otherwise. The probability of product returns for the transaction recovered by email 'i', conditional on a set of covariates X, is expressed as

$$(5)\ \Pr(ProductReturns|X_i, \beta^{pr}) = \frac{\exp(X_i\beta^{pr})}{1+\exp(X_i\beta^{pr})}$$

The general specification of the covariates for all four models (equations 2 - 5) is given as:

$$\begin{aligned} X_i\beta^m = \beta_0^m &+ \beta_1^m Open.NoDisc_i + \beta_2^m Open.Disc_i + \beta_3^m Cust_i + \beta_4^m Cart_i \\ &+ \beta_5^m Open.NoDisc_i \times Cust_i + \beta_6^m Open.Disc_i \times Cust_i \\ &+ \beta_7^m Open.NoDisc_i \times Cart_i + \beta_8^m Open.Disc_i \times Cart_i \\ &+ \beta_9^m Duration_i + \beta_{10}^m Controls_i \end{aligned}$$

In the equation, β^m is the vector of parameters to be estimated. Since each model is estimated separately, m is represented by r in the Revisit model, c in the Conversion model, v in the Value Recovered model, and pr in the Product Returns model. The intercept, β_0^m, is only included in the Value Recovered and Product

Returns models, since the constant term is already captured by the baseline hazard function in the Revisit and Conversion proportional hazard models.

I used emails that were not opened as the base level, and included two indicator variables, *Open.NoDisc* (=1 if customers open emails that did not offer a discount, 0 if the emails they opened offered a discount or if they did not open the email) and *Open.Disc* (=1 if customers open emails that offered a discount, 0 if the emails they opened did not offer a discount or if they did not open the email). Thus, the coefficients for *Open.NoDisc* captures the difference in levels of the dependent variables among customers who opened emails relative to customers who did not open the emails. Since customers would only be aware of the discount after opening the emails, I can isolate the effects of incentives by comparing the coefficients between *Open.NoDisc* and *Open.Disc*.

Cust is a vector capturing the four customer characteristics of interest (i.e., *CouponProne, ValueConscious, AveTransSize, PrdReturns* to represent coupon-proneness, value-consciousness, average size of past transactions, and product returns behavior respectively), and *Cart* is a vector capturing the three cart characteristics of interest (i.e., *NumItems, AveItemPrice,* and *PrcntExclusive* to represent number of items in the abandoned cart, average price of the items, and percentage of exclusive items in the cart). In addition, I interacted these customer and cart characteristics with the two indicator variables *Open.NoDisc* and *Open.Disc*. The duration from the time of cart abandonment to the time the email was received was also included (i.e., *Duration*) to represent the first point of contact between the retailer and the owner of the abandoned cart. Since duration is skewed, I use the logarithm of duration (e.g., Mallapragada, Chandukala and Liu 2016).

A vector of controls is included to account for other potentially confounding variables. I included common metrics in the customer relationship management literature such as length of relationship with the retailer, recency and frequency of transactions, and number of previous transactions to account for heterogeneity in customers’ relationship with the retailer. As browsing behavior can serve as an indication of customers’ interest and engagement in the purchase decision (Danaher, Mullarkey, and Essegaier 2006; Mallapragada, Chandukala and Liu 2016), I control for browsing behavior during the abandoned session by including measures of cart activity, session duration, and recent browsing duration prior to the abandoned session. Following prior research, I used the logarithm for session and recent browsing durations to accommodate the right-skewed nature of the data. Research from the industry has found that the device used (i.e., desktop, mobile devices) affect conversion rates (eMarketer 2017e). Thus, I also include indicator variables to represent the device used during the abandoned session (for all models), revisit session (for the Conversion model) and session in which the purchase was made (for the Value Recovered and Product Returns models). Lastly, I include variables to control for the composition of product categories in the abandoned cart and emails received by customers in the past month. Table 2.3 details how the customer and cart characteristics, as well as other control variables are operationalized.

Table 2.3 Variable Operationalization

Variable	Operationalization
Customer Characteristics	
CouponProne	Number of transactions with coupon divided by total number of transactions
ValueConscious	Number of sale items purchased divided by total number of items purchased
AveTransSize	Sum of value of all transactions divided by cumulative number of transactions
PrdReturns	Number of items returned divided by total number of items purchased
Cart Characteristics	
NumItems	Total number of items in the cart when it was abandoned
AveItemPrice	Average price of items in the cart when it was abandoned
PrcntExclusive	Number of exlusive items divided by total number of items in the cart when it was abandoned
Control Variables	
FirstOrder	Number of weeks from first transaction
LastOrder	Number of weeks from the most recent transaction
Frequency	Number of transactions divided by number of weeks from first transaction
NumOrders	Number of transactions customer has made with the retailer
PrcntApparel; PrcntFootwear; PrcntAccessories	Number of items in subcategory (i.e., apparel, footwear, and accessories respectively) divided by total number of items in the cart when it was abandoned
DeviceAbandoned; DeviceRevisit; DeviceOrder	Dummy variable, with 0 if a desktop was used, and 1 if a mobile device (i.e., phone or tablet) was used during the abandoned session, revisit session, or session when order was made.
SessionDuration	Logarithm of the duration from start of the session to the last cart activity
SessionActivity	Total number of items added to or removed from the cart during the abandoned session
RecentBrowsing	Logarithm of the sum of durations across all sessions in the past 2 weeks prior to cart abandonment
EmailControls	Vector of variables controlling for number of emails from retailer, number of recovery interventions, and number of emails with incentives received in the past 1 month

2.5 Results

The results discussion focuses on the standardized parameter estimates to enable comparison across the different models and facilitate interpretation of effects. Interpretation of the standardized coefficients in the proportional hazards regression is similar to a multiple regression model, with the standardized coefficients representing change in the expected log of the hazard ratio when the corresponding covariate increase by one standard deviation, holding all other covariates constant. The model statistics and standardized coefficients of key variables for the four models are presented in Table 2.4.

2.5.1 Effects of Incentives

The coefficients of *Open.NoDisc* (.167, $p < .01$) and *Open.Disc* (.171, $p < .01$) in the Revisit model are significantly positive (relative to the base level of emails that were not opened), and the exponentiated coefficients are 1.181 and 1.187 respectively, implying that customers who open emails have an 18% increase in hazard of revisiting the retailer. The coefficients are very close in magnitude, suggesting that regardless of the presence of incentives, customers are similarly likely to revisit the retailer after opening emails.

In the Conversion model, compared to the coefficient of *Open.NoDisc* (.091, $p < .10$), the coefficient of *Open.Disc* is positive and highly significant (.136, $p < .01$) with an exponentiated coefficient of 1.146, indicating that customers who are exposed to incentives have a 15% increase in hazard of purchasing upon revisiting. Thus, incentives are effective in converting revisits to purchases.

Table 2.4 Standardized Parameter Estimates of Main and Interaction Effects

	Revisit	Conversion	Value Recovered	Product Returns
Main effects				
Open.NoDisc	.167*** (.038)	.091* (.048)	2.252 (3.903)	.087 (.161)
Open.Disc	.171*** (.038)	.136*** (.049)	1.773 (3.626)	.053 (.156)
Interactions effects				
CouponProne (base=NotOpen)	.007 (.008)	-.027** (.011)	4.249*** (1.005)	.291*** (.042)
CouponProne × Open.NoDisc	-.015 (.025)	-.073** (.030)	-2.642 (2.538)	-.068 (.103)
CouponProne × Open.Disc	-.033 (.024)	.034 (.030)	-.761 (2.441)	-.064 (.099)
ValueConscious (base=NotOpen)	.009 (.008)	-.017 (.011)	-1.922* (1.018)	.057 (.045)
ValueConscious × Open.NoDisc	.022 (.024)	.056* (.030)	1.493 (2.551)	.090 (.107)
ValueConscious × Open.Disc	.015 (.025)	.002 (.030)	4.791** (2.352)	.026 (.099)
AveTransSize (base=NotOpen)	-.028*** (.009)	-.029*** (.011)	36.404*** (.967)	.082* (.042)
AveTransSize × Open.NoDisc	-.035 (.028)	.094*** (.033)	-4.024 (2.763)	.122 (.121)
AveTransSize × Open.Disc	-.047* (.027)	.101*** (.035)	7.074*** (2.610)	.023 (.112)
PrdReturns (base=NotOpen)	.027*** (.008)	.151*** (.011)	-.932 (.995)	1.255*** (.046)
PrdReturns × Open.NoDisc	-.014 (.023)	-.063** (.028)	2.033 (2.400)	-.214** (.106)
PrdReturns × Open.Disc	-.024 (.023)	-.039 (.027)	1.522 (2.372)	-.228** (.104)
NumItems (base=NotOpen)	.055*** (.008)	-.104*** (.016)	7.614*** (1.120)	.063 (.046)
NumItems × Open.NoDisc	.005 (.019)	-.066 (.050)	-6.279*** (1.827)	-.067 (.071)
NumItems × Open.Disc	.104*** (.030)	-.044 (.052)	-2.707 (2.673)	-.239* (.135)
AveItemPrice (base=NotOpen)	-.001** (.000)	-.002*** (.001)	.489*** (.043)	-.001 (.002)
AveItemPrice × Open.NoDisc	.000 (.001)	.003** (.001)	-.093 (.100)	.001 (.004)
AveItemPrice × Open.Disc	.003*** (.001)	.002 (.001)	-.044 (.094)	.001 (.004)
PrcntExclusive (base=NotOpen)	-.014 (.009)	-.015 (.011)	1.217 (1.026)	.108** (.045)
PrcntExclusive × Open.NoDisc	-.023 (.024)	.009 (.030)	-2.849 (2.488)	-.056 (.100)
PrcntExclusive × Open.Disc	.035 (.024)	-.012 (.029)	2.557 (2.402)	-.152 (.097)
Observations	22,058	14,633	5,941	5,941
Model fit	Log-likelihood = -187,348.5	Log-likelihood = -108,314.2	Adjusted R-square = 0.3256	Log-likelihood = -2773.4

** p ≤ .10; ** p ≤ .05; *** p ≤ .01;*

Note:

(1) Numbers in parentheses are standard errors of the estimates.
(2) Base level = Email interventions that were not opened.
(3) Coefficients of control variables are presented in Appendix B.

2.5.2 Effects of Customer Characteristics

Coupon-proneness. The coefficient for *CouponProne* is negative in the Conversion model (-.027, $p < .05$), indicating that among customers who did not open the emails (i.e., base level), coupon-prone customers are less likely to purchase after revisiting the retailer. Interestingly, while the interaction between *CouponProne* and *Open.Disc* is not significant, the interaction between *CouponProne* and *Open.NoDisc* is significantly negative (-.073, $p < .05$), suggesting that coupon-prone customers who opened emails that did not contain incentives are even less likely to make a purchase compared to coupon-prone customers who did not open emails. Even though recovered transactions among coupon-prone customers have higher Value Recovered (4.249, $p < .01$), these customers also have a higher likelihood of making Product Returns (.291, $p < .01$).

Value-consciousness. In contrast, value-conscious customers who frequently purchase sale items respond differently to incentives. While interactions between *ValueConscious* and *Open.Disc* are not significant in the Revisit and Conversion models, the interaction is significantly positive in the Value Recovered model (4.791, p, < .05), implying that value-conscious customers are likely to purchase even more in the presence of a discount, which is in line with prior expectations.

Average size of previous transactions. The coefficients for *AveTransSize* is negative in the Revisit (-.028, p < .01) and Conversion models (-.029, p < .01), indicating that customers who make large purchases in previous transactions are less likely to revisit and purchase. These customers could be accumulating products to purchase in a single occasion to minimize the inconvenience of receiving multiple product deliveries. The interactions between *AveTranSize* and *Open.NoDisc* (.094, $p < .01$) and *Open.Disc* (.101, $p < .01$) in the Conversion model are significantly positive, implying that as the size of previous transactions increase, the likelihood of purchasing upon revisiting the retailer is higher if customers open the emails. However, the coefficients for these two interaction terms are similar in magnitude, suggesting that the presence of incentives does not alter the relationship between average size of previous transactions and the probability of conversion upon revisiting. Average size of previous transactions is a very strong predictor of Value Recovered (36.404, $p < .01$). In addition, the interaction between *AveTransSize* and *Open.Disc* is significantly positive (7.074, $p < .01$), implying that as customers' average size of previous transaction increase, they are likely to purchase even more in the presence of incentives.

Product return behavior. The proportion of previous product returns positively influences Revisit (.027, $p < .01$) and Conversion (.151, $p < .01$), implying that product returns may facilitate cart recovery by reducing risk (Petersen and Kumar 2015). The interaction between *PrdReturns* and *Open.NoDisc* is significantly negative in the Conversion model (-.063, $p < .05$), indicating that in the absence of incentives, customers with high proportions of previous product returns are less likely to purchase upon revisiting the retailer after opening emails. Consistent with prior research suggesting that post-purchase product returns is a recurring behavior (Shah, Kumar and Kim 2014), customers with high proportion of previous product returns are also more likely to return products from the recovered transaction (1.255, p, $< .01$). Interactions between *PrdReturns* and *Open.NoDisc* (-.214, $p < .05$) and *Open.Disc* (-.228, $p < .05$) are both significantly negative in the Product Returns model, with similar magnitude. This finding suggests that customers with a high proportion of previous product returns are less likely to return products if they open emails interventions, but the presence of incentives does not moderate the relationship between previous product return behavior and the probability of product returns in the recovered transaction.

2.5.3 Effects of Cart Characteristics

Average price of cart items. The coefficient for *AveItemPrice* is significantly negative in the Revisit (-.001, p <.01) and Conversion models (-.002, p <.01), indicating customers with more expensive items in the abandoned carts are less likely to revisit the retailer, and less likely to purchase upon revisiting. The interaction between *AveItemPrice* and *Open.Disc* is significantly positive in the Revisit model (.003, p < .01). Thus, customers with more expensive items in their abandoned carts are more likely to revisit the retailer when incentives are offered. The interaction between *AveItemPrice* and *Open.Disc* is not significant (.002, p > .10) relative to the baseline of customers who did not open emails, while the interaction between *AveItemPrice* with *Open.NoDisc* is significantly positive (.003, p < .05). However, when *Open.NoDisc* was used as the base level, the interaction between *AveItemPrice* and *Open.Disc* failed to reach significance relative to this new base level (-.001, p > .618), implying that the relationship between average price of items in the abandoned cart and the probability of conversion did not differ among customers who received a discount and those who did not.

Number of cart items. The coefficient for *NumItems* is significantly positive in the Revisit model (.055, p < .01). Thus, customers are more likely to revisit the retailer as the number of products in their abandoned carts increases. The interaction between *NumItems* and *Open.Disc* is significantly positive in the Revisit model (.104, p < .01), suggesting that when incentives are offered, customers with more items in their abandoned carts are even more likely to revisit the retailer. *NumItems* has a negative relationship with Conversion (-.104, p <.01), but a positive relationship with Value Recovered (7.614, p <.01), indicating that as the number of items in the abandoned cart increase, customers are less likely to purchase upon revisiting the retailer, but the value of transactions would be higher if they are successfully recovered. Furthermore, the interaction between *NumItems* and *Open.NoDisc* is significantly negative in the Value Recovered model (-6.279, p < .01), while the interaction with *Open.Disc* is not significant. This finding suggests that customers with more items in the abandoned cart eventually purchase less items if they did not receive an incentive.

Proportion of exclusive products. I find that carts with a higher proportion of exclusive products have a higher probability of product returns (.108, p <.05). A large majority of these exclusive products are the retailer's private label items. Unlike international brands that the retailer carries, private label items are not sold in offline channels. Hence, customers purchasing private label items are unable to ascertain the appropriate sizes before purchasing, and are consequently more likely to return the items. Contrary to expectations, incentives does not appear to moderate the relationship between the proportion of private labels in abandoned carts and responsiveness to recovery interventions.

2.5.4 Effects of Control Variables

In general, the effects of control variables, presented in Table 2.5, are largely consistent with general intuition or findings from prior literature, lending confidence to the validity of the results. For example, I find that as duration from last purchase increases (i.e., *LastOrder*), customers are less likely to revisit or purchase after receiving recovery interventions (-.068 in the Revisit model and -.168 in the

Conversion model, $p < .01$ for both). In contrast, responsiveness to interventions increase as the length of relationship (i.e., *FirstOrder*, .020 in the Revisit model and .029 in the Conversion model, $p < .05$ for both) and experience with the retailer (i.e., *NumOrders*, .103 in the Revisit model and .131 in the Conversion model, $p < .01$ for both) increase. I also find that as the percentage of apparel (.232, $p < .01$) and footwear (.116, $p < .10$) increase, the probability of post-purchase product returns increase, reflecting the importance of product fit in these categories.

Table 2.5 Standardized Parameter Estimates of Control Variables

	Revisit	**Conversion**	**Value Recovered**	**Product Returns**
Duration	-.126*** (.007)	-.088*** (.009)	-.954 (.795)	-.002 (.033)
Customer Characteristics				
FirstOrder	.020** (.009)	.029** (.012)	1.429 (1.022)	.160*** (.044)
LastOrder	-.068*** (.008)	-.168*** (.012)	2.793*** (.913)	.094** (.038)
NumOrders	.103*** (.008)	.131*** (.011)	2.158* (1.173)	-.007 (.048)
Frequency	-.009 (.011)	.042*** (.015)	-.311 (1.140)	.083* (.047)
Cart Characteristics				
PrcntApparel	.035** (.014)	.019 (.019)	.344 (1.617)	.232*** (.074)
PrcntAccessories	.010 (.011)	-.003 (.015)	-2.326* (1.277)	-.064 (.061)
PrcntFootwear	.016 (.012)	.017 (.016)	-.782 (1.344)	.116* (.061)
Browsing Characteristics				
DeviceAbandoned = Mobile	.145*** (.053)	.007 (.075)	-1.681 (5.704)	-.135 (.228)
DeviceRevisit = Mobile	-	-.662*** (.048)	-	-
DeviceOrder = Mobile	-		-8.638*** (2.705)	-.024 (.109)
SessionDuration	.077*** (.007)	.033*** (.009)	2.198*** (.820)	.048 (.034)
SessionActivity	-.015** (.006)	.052*** (.014)	1.075 (.846)	.020 (.034)
RecentBrowsing	.264*** (.009)	.053*** (.011)	2.218** (.990)	.021 (.042)
Observations	22,058	14,633	5,941	5,941
Model fit	Log-likelihood = -187,348.5	Log-likelihood = -108,314.2	Adjusted R-square = 0.3256	Log-likelihood = -2,773.4

** $p \leq .10$; ** $p \leq .05$; *** $p \leq .01$;*

Note:

(1) Numbers in parentheses are standard errors of the estimates

(2) Device Revisit is excluded from Value Recovered and Product Returns models due to high correlation with Device Order.

The results also indicate that customers who abandoned their carts on mobile devices are more likely to revisit the retailer after receiving interventions (.145, $p < .01$), but customers who revisit on mobile devices are less likely to make a purchase (-.662, $p < .01$). Furthermore, customers who make purchases on mobile devices spend less (-8.638, $p < .01$). Consistent with extant research proposing browsing duration as indicative of consumers' interest and engagement (Danaher, Mullarkey, and Essegaier 2006; Mallapragada, Chandukala and Liu 2016), I find that duration of the abandoned session and recent browsing duration are positively associated with Revisit (.077 and .264 respectively, $p < .01$ for both), Conversion (.033 and .053 respectively, $p < .01$ for both), and Value Recovered (2.198, $p < .01$ and 2.218, $p < .05$ respectively). In addition, the coefficient for Duration is negative in the Revisit model (-.126, $p < .01$) and Conversion model (-.088, $p < .01$), suggesting that likelihood of cart recovery declines as duration from abandonment increases.

2.5.5 Financial Implications of Offering Incentives

A critical issue online retail managers face is to understand the impact of discounts on profit margins, and at what point it would be feasible to offer discounts to recover abandoned carts. To tackle this issue and aid managerial decision making, I conducted three additional analyses. Firstly, I determine the minimum required gross margin for a 15% discount to generate incremental profit (relative to not offering any discounts) for the retailer in this study. At a minimum, retailers' gross margins should be above the amount of discount offered (i.e., 15%) to break even by offering discount. However, even with gross margins above the discount amount, retailers may be better off not offering discount if profit from the additional transactions recovered with discount is lower than the loss in potential profits as a result of offering the discount. To determine the critical point at which retailers would be better off not offering a 15% discount, I used the recovery rates and average recovered revenues from the study to perform a back-of-the-envelope calculation by comparing total recovered profit from offering a 15% discount vs not offering a discount at various levels of gross margins (Table 2.6). The calculations suggest that for a 15% discount to be financially viable, the retailer should have a gross margin of at least 56.5% before offering discounts.

Table 2.6 Minimum Gross Margin Required to Profit From 15% Discount

Gross Margin Before Discount (%)	Incremental Profit With 15% Discount (vs No Discount) (%)
20.0%	-65.9%
30.0%	-31.9%
40.0%	-14.8%
50.0%	-4.6%
56.5%	0.0%
60.0%	2.2%
70.0%	7.1%
80.0%	10.7%
90.0%	13.6%

Secondly, I also consider how the minimum gross margin required changes as the effectiveness of discounts vary by determining the critical point at varying levels of Recovery Rate and Recovered Revenue (Table 2.7). The ratio of Recovery Rate when a 15% discount is offered vs when no discount is offered represents the effectiveness of discounts in recovering transactions – a ratio of 1 indicates that the Recovery Rate in both conditions are the same, in which case, the discount is ineffective. Similarly, the ratio of Recovered Revenue when a 15% discount is offered vs when no discount is offered represents the effectiveness of discounts in encouraging higher spending among transactions that are recovered. In the calculations, Recovered Revenue refers to the total amount paid by customers (i.e., if a discount is offered, the Revenue Recovered is the price paid after accounting for the discount). Hence, if the ratio of Recovered Revenue equals 1, customers are paying as much even with a 15% discount. A ratio of Recovered Revenue equivalent to 0.85 reflects the special case when the value of items purchased by customers are the same with or without discount, but the amount eventually paid is reduced due to the 15% discount.

Table 2.7 Minimum Gross Margin Required to Profit From 15% Discount at Varying Levels of Recovery Rates and Recovered Revenues

Ratio of Recovery Rate With 15% Discount vs No Discount	**Ratio of Recovered Revenue With 15% Discount vs No Discount**							
	0.85	**0.90**	**0.95**	**1.00**	**1.05**	**1.10**	**1.15**	**1.20**
1.00					78.8%	66.0%	57.5%	51.5%
1.05				78.8%	65.5%	56.9%	50.7%	46.1%
1.10			80.4%	66.0%	$\boxed{56.9\%}$	50.5%	45.8%	42.2%
1.15		84.0%	67.6%	57.5%	50.7%	45.8%	42.0%	39.1%
1.20	90.0%	70.5%	59.0%	51.5%	46.1%	42.2%	39.1%	36.7%

As highlighted in Table 2.7, in the present research context (approximately 1.10 ratio of Recovery Rate and 1.05 ratio of Recovered Revenue with and without discounts, respectively), the minimum gross margin required is approximately 56.9%, which is very close to the number presented in Table 2.6. As the ratio of Recovery Rate and Recovered Revenue with and without discounts increases, the required gross margin to enjoy incremental profit reduces. For example, if the ratio of Recovery Rate with and without discounts was 1.20 and the ratio of Recovered Revenue with and without the 15% discount was 1.05 then the firm can offer a 15% discount to recover abandon carts as long as the profit margin is greater than 42.2%. Thus, by calculating their own ratio of Recovery Rates and Recovered Revenues, retailers can refer to Table 2.7 to determine the minimum gross margin required for a 15% discount to be a financially viable option.

Finally, I compute the range of minimum gross margins required for varying levels of Revisit Rates and Conversion Rates. Since Recovery Rate is a product of Revisit and Conversion Rates, Table 2.8 is symmetric. In the current empirical context, the ratio of Revisit Rate when a 15% discount is offered vs when no discount is offered is close to 1, but in cases when discount improves Revisit Rate, the minimum gross margin required for discounts to generate incremental profits would be in the range of 40-50% (with the Conversion Rate at 1.10). For the same Conversion Rate, as the Revisit Rate goes up, the retailer would require a lower profit margin to ensure financial feasibility of the discount. I believe that these calculations will make the findings more generalizable and help retailers decide if it will be viable for them to offer incentives to recover abandoned carts.

Table 2.8 Minimum Gross Margin Required to Profit From 15% Discount at Varying Levels of Revisit and Conversion Rates

Ratio of Revisit Rate With 15% Discount vs No Discount	**Ratio of Conversion Rate With 15% Discount vs No Discount**				
	1.00	**1.05**	**1.10**	**1.15**	**1.20**
1.00	81.1%	67.1%	57.9%	51.5%	46.8%
1.05	67.1%	57.6%	51.0%	46.2%	42.5%
1.10	57.9%	51.0%	46.0%	42.2%	39.3%
1.15	51.5%	46.2%	42.2%	39.1%	36.7%
1.20	46.8%	42.5%	39.3%	36.7%	34.6%

2.6 Conclusion

Despite the prevalence of online shopping cart abandonment, there has been a paucity of research on intervention strategies to recover these abandoned carts. By examining the impact of incentives along stages of the recovery process and the moderating influence of various customer and cart characteristics, the present research represents an initial step to address this void.

Findings from the field experiment revealed that among the retailer's most profitable customers those who receive incentives are more likely to purchase upon revisiting the retailer. Coupon-prone customers are less likely to purchase if they open email interventions that do not contain incentives, while value-conscious customers and customers with larger transaction size (based on previous transactions) purchase even more when they are given a discount. Additionally, incentives moderate the relationship between the type of device and the different stages of cart recovery.

2.6.1 Managerial Implications

Depending on retailers' business objectives (i.e., to increase revisits, conversions, or value recovered from transactions), they can strategically offer incentives or focus recovery efforts to target different segments of customers using insight from this research. I condense findings from this study to offer a few recommendations for designing recovery interventions that are more effective.

Encouraging revisits after cart abandonment. In the study, customers who opened emails were more likely to revisit the retailer, regardless of the presence of incentives. While I did not examine the incremental impact of recovery interventions (vs. no interventions), Moriguchi, Xiong and Luo (2016) found that sending emails to remind customers about items left behind in their carts significantly improved purchase rate even when no incentive or new information is provided. Other researchers have similarly demonstrated that interventions can increase purchase intentions by increasing brand salience (Bart, Stephen, and Sarvary 2014; Lovett and Staelin 2016; Sahni, Zou and Chintagunta 2016). Thus, even without any financial incentives, recovery interventions may be sufficient to improve revisit rates by triggering recall for abandoned cart items. Hence, retailers with healthy conversion rates but poor revisit rates may want to avoid using incentives, as doing so could reduce potential profits.

Improving conversion among customers who revisit. Findings from this research consistently show that customers who receive incentives are more likely to purchase after revisiting the retailer. Thus, retailers struggling with poor conversion rates could offer incentives to improve conversion. Nevertheless, incentives should be used judiciously because over-reliance on incentives could train customers to abandon their carts in anticipation of incentives, thus reducing future profits (SaleCycle 2017). In this study, I found that coupon-prone customers who opened emails that did not contain incentives were even less likely to purchase compared to those who did not open emails; this finding may be an indication of the learning behavior among coupon-prone customers.

Increasing value from recovered transactions. Reassuringly, value of recovered transactions does not appear to be reduced with the use of incentives as expected – customers who received incentives spent as much as those who did not. To increase value recovered from transactions, retailers should offer incentives to customers with higher average transaction size (based on past transactions) and customers who purchase a high proportion of sale items, as these customers are likely to purchase even more in the presence of incentives. I also find that customers who spend more time browsing prior to cart abandonment and during the abandoned session are likely to purchase more, so retailers may want to focus their recovery efforts based on browsing behavior.

Reducing product returns from recovered transactions. While transactions recovered from coupon-prone customers are higher, these customers also have a higher likelihood of returning products post-purchase. Coupon-prone customers could be more likely to engage in impulse purchases resulting from their desire to take advantage of discounts, even if the items do not satisfy their needs. Subsequently, these customers may experience greater post-purchase regret, leading to higher product returns. Thus, retailers need to be wary of targeting these customers in their recovery interventions. Additionally, even though customers with high proportion of product returns are more responsive to recovery interventions (in terms of revisits and conversions), they are also more likely to return products. Research has shown that customers with excessive product returns generate more losses as they purchase more products, and may consequently be unprofitable to firms (Shah et al. 2012, Shah, Kumar and Kim 2014). To that end, Shah et al. (2012) have suggested that firms may want to avoid cross-selling to customers with high proportions of product returns. In the context of cart recovery, firms may similarly want to avoid sending recovery interventions to customers with an excessive amount of product returns.

Timing of recovery interventions. Findings from this study suggest that retailers should establish contact with customers soon after abandonment. As the duration from cart abandonment increases, owners of abandoned carts have more opportunity to search for other alternatives, or may no longer find the product relevant and hence, would have a lower likelihood of being recovered. This finding echoes research from the industry, which advocate sending out recovery interventions within the first few hours of cart abandonment (eMarketer 2016; SaleCycle 2017; Webtrends 2012).

Impact of mobile device usage on cart recovery. I find that device used during each stage of the recovery process has an influence on the subsequent stage. In particular, customers who revisit on mobile devices are less likely to make a purchase, and customers who make purchases on mobile devices spend less. These findings suggest that retailers could potentially improve conversion and increase transaction size by encouraging customers to revisit and purchase on desktops. Strategies to influence device usage is beyond the scope of this study, and presents an opportunity for future research. Importantly, retailers encouraging customers to migrate to app platforms (which are only available on mobile devices) should be cognizant of the potential implications of device usage on cart abandonment and recovery.

Findings from this research equipped the focal retailer with a better understanding of the cart recovery process, and enabled them to assess the effectiveness of incentives in their recovery interventions. The research approach can be tailored by industry practitioners to examine how their existing interventions affect customers' progression along the recovery process. Guided by findings from this research, retailers can strategically reach out to segments of customers to improve recovery rates and maximize revenues.

2.6.2 Contributions

The present research offers a valuable addition to the online retailing literature. Building on established online purchase funnels (e.g., Hu, Du and Damangir 2014; Li and Kannan 2014; Wiesel, Pauwel and Arts 2011), I examined the funnel in the modified context of recovering abandoned carts, and extended it to incorporate post-purchase product returns. By disentangling the recovery process to assess effectiveness of recovery interventions, this research examines the role of incentives to facilitate conversion in the cart recovery process. In addition, this research provides empirical evidence of the moderating effects of incentives on several customer and cart characteristics in the cart recovery process.

Findings from this study also highlight important distinctions between coupon-prone customers (i.e., customers with high proportion of orders with coupons) and value-conscious customers (i.e., customers who purchase a high proportion of sale items). In particular, relative to coupon-prone customers who did not open recovery interventions, coupon-prone customers who open recovery interventions that did not contain incentives are less likely to purchase. In contrast, while incentives did not improve revisit and conversion rate among value-conscious customers, those who were eventually recovered purchased even more when they were offered a discount. These findings are consistent with prior work on coupon-proneness and value-consciousness (Lichtenstein, Netemeyer, and Burton 1990; Pillai and Kumar 2012). Seen through this lens, the current study extends discussion on the distinction between coupon-proneness and value-consciousness by providing empirical evidence of their diverging effects.

2.6.3 Limitations and Research Extensions

I acknowledge a few limitations in this study arising primarily due to the nature of the data. As with other studies that rely on unique user identification, the data only captures cart activities performed when the customer logs in with a user account. Hence, revisits to the retailer may be omitted from the data set if the customer did not log in while browsing. The present study also uses data from a single online retailer in the fashion industry. As the effects of recovery interventions might differ based on industry (e.g., online grocery stores, online book stores), characteristics of product (e.g., utilitarian vs hedonic, Mallapragada, Chandukala and Liu 2016), retailer reputation (e.g., Moore and Mathews 2006), or browsing device (Business Insider 2016; Forbes 2013), further research could extend the study across different contexts to assess the generalizability of findings. This study also focuses on a segment of customers (i.e., the retailer's most profitable customers) to reduce unobserved heterogeneity, and the effects may vary for other customer segments (e.g., new customers, lapse customers, less-profitable customers).

While the present study focuses on percentage discounts in recovery interventions, the impact of other types of incentives (e.g., free gift, free shipping) on cart recovery may differ, and could be a worthwhile avenue for further research. Notwithstanding these limitations, I believe that findings from this study would resolve some uncertainty surrounding the use of email recovery interventions and help marketing managers design recovery interventions that are most appropriate.

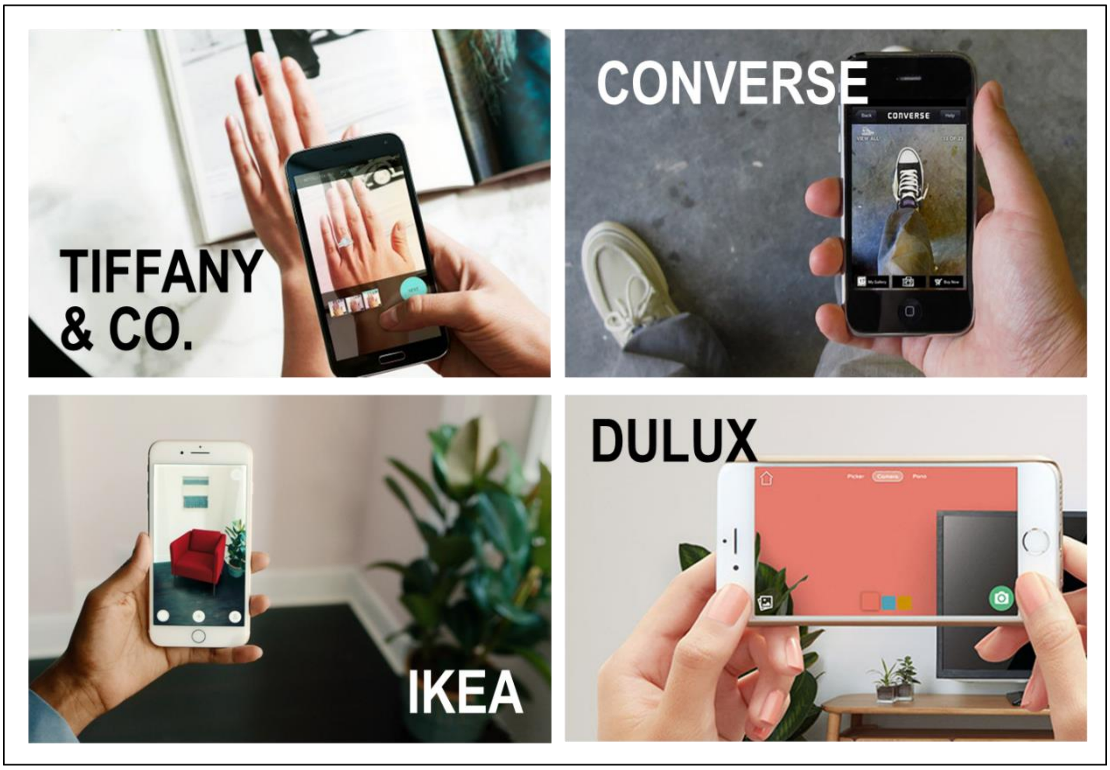
3. Augmented Reality in Online Retail

3.1 Introduction

Research has emphasized the importance of direct product experience because it allows customers to learn about product benefits and assess product fit (e.g., Bell et al. 2018, Chandukala et al. 2017). Reflecting the importance of direct product experience, extant research on product sampling has demonstrated its impact on short and long-term sales, and its ability to expand the category by increasing purchase probabilities among customers who would not have purchased without a sample (Bawa and Shoemaker 2004; Chandukala, Dotson, and Liu 2017; Lammers 1991). In online contexts, Bell, Gallino, and Moreno (2018) found positive effects on customer demand when online-first retailers introduce offline showrooms (locations that let customers view and try physical products, but do not perform order fulfillment functions, e.g., Warby Parker). However, for most online retailers, providing direct product experience is a logistical challenge.

With the introduction of Augmented Reality (AR), a technology that superimposes virtual objects onto a live view of physical environments, it now becomes feasible for customers to experience products virtually. This technology helps users visualize how virtual objects fit into their physical reality, and opens the possibility for customers to assess product fit in the absence of physical products (refer to Figure 3.1 for examples). For example, Amazon and Ikea uses this technology to help customers determine if electronic products or furniture pieces fit with their existing room décor; Tiffany & Co. uses AR to help shoppers visualize how engagement rings will look like on their hand; and beauty and cosmetic retailers, L'Oréal and Sephora, use AR to give customers a preview of their appearance when wearing various cosmetic products. These examples illustrate the promising potential of AR in online retail to manage product expectations and instill purchase confidence (Porter and Heppelmann 2017). With the launch of AR toolkits by technology giants Apple and Google in 2017, it is now easier for companies to develop their own mobile apps with AR feature. Furthermore, Facebook has started testing AR-enabled display ads on their News Feed, making the technology even more accessible to companies.

Figure 3.1 Examples of Augmented Reality in Retail



Despite the interest in, and importance of, AR in marketing contexts, there has been limited research examining how customers respond to AR in the real world. Even though more than 40% of executives from leading global brands plan to make significant investments in AR/VR (KPMG 2017), close to 30% of marketing managers identified AR/VR as the technology they are most unprepared for, second only to artificial intelligence (eMarketer 2017b). While AR communicates visual information about products, it is unable to convey other experiential product attributes (e.g., product texture, taste or scent) and hence, its impact on product preference and purchase is still unclear.

Given the promising potential of AR and the lack of clarity surrounding its application in marketing contexts, the present research aims to provide a better understanding of how retailers can leverage this emerging technology to improve customer engagement and increase purchase. Stated concisely, I intend to address the following questions:

1. How does AR usage affect in-app engagement, and how does this vary by customer segments?
2. How does AR usage influence purchase? How does it influence product and brand preference?
3. Can AR induce previously offline customers to start purchasing online by replicating the in-store experience of trying products?

As AR is mainly experienced on mobile apps (eMarketer 2018a), I focus on AR usage on the mobile app platform. Data was obtained from an international cosmetics retailer who incorporated AR into their mobile app. The AR technology helps customers realistically visualize how they look with different cosmetic products (e.g., lipsticks, eye liners) by superimposing the selected products on a live view of customers' face. As the AR feature was introduced at different times for different product categories (due to factors relating to adaptation of the technology for different facial features), I took advantage of this natural experiment in my research to account for self-selection in customers' decision to use the AR feature. App activity data from close to 200,000 browsing sessions for over 63,000 customers and 2,800 unique products were collected across an 8-month period, leading to more than 1.5 million customer-session-product-level observations. By combining this data with detailed product information and customers' transaction history, I am able to examine how AR's influence varies by product and customer characteristics.

To give a preview of the findings, customers who use AR spend 52.6% more time on the app and view 3.3 times more products on average. Additionally, session purchase rate is 14.7% higher when customers use AR, with the increase coming mainly from customers who have previously purchased online with the retailer. I find that AR has a stronger influence on purchase for lower-priced products and less-popular brands with lower share of sales, suggesting that virtual product experience reduces customers' reliance on price and brand as extrinsic product quality cues. Additionally, AR is particularly effective at increasing consideration and purchase for products or brands that customers have never purchased before.

The present research represents an initial step to understand how virtual product experience via AR can influence customer engagement and purchase in online retail, and makes several contributions to the field. Firstly, to the best of my knowledge, this is the first study to document customers' real-world interactions with AR, and its subsequent influence on actual purchases. Secondly, I demonstrate how the ability to experience products virtually diminishes the importance customers place on extrinsic cues such as price and brand popularity. This implication suggests that AR could alter the way customers make online purchase decisions, and potentially level the playing field for brands or products at the long tail of the product sales distribution (see Brynjolfsson et al. 2010). Thirdly, I show that AR usage increases consideration for products and brands customers have never purchased before by helping them discover these products more easily. Lastly, given the pervasive challenge of sustaining customers' interest on mobile app platforms, my findings suggest that AR could potentially help online retailers engage customers and increase time spent on retail apps.

3.2 Background of Augmented Reality

3.2.1 Augmented Reality Technology

Augmented reality (AR) integrates virtual elements into real-world environments to create alternate perceptions of reality. Using sensors and object-recognition capabilities from input devices such as cameras, AR technology scans the physical environment, identifies features in the environment, and super-imposes digital objects (e.g., 2 or 3-dimensional images or animations, text, sounds) on top of a live view of the real-world. By blending virtual elements into physical environments in real-time, AR enriches users' visual and auditory perceptions of reality. In most cases, the virtual elements are responsive to movements or gestures, creating an interactive experience for users.

Even though the technology is still in its growth phase, leaders in the field, including Apple CEO, Tim Cook (Independent 2017; Vogue 2017), and Google's Director of Virtual Reality (VR) and AR, Greg Jones (Forbes 2017), have lauded its potential to transform the retail experience. By blending the shopping experience with interactive digital elements, augmented reality presents marketers with new opportunities to engage shoppers and redefine the brand experience.

Although AR is often classified together with virtual reality (VR), the two technologies are distinct, both in the way they function and the way they are experienced. Unlike AR, which receives input from the real world and adds digital elements to it, VR immerses users in a completely digital environment - users are virtually transported to an artificial, simulated world, and is entirely shut out from their surroundings. Due to the expensive headsets required and the disorienting experience of being entirely isolated from the real world (Ericsson 2017), the appeal of VR has been largely limited to industries with products high in simulated content, such as gaming and entertainment (Forbes 2018). As a result, adoption of the technology has been slow, with less than 15% of internet users expressing interest in VR (eMarketer 2017f). In contrast, as AR is anchored in the physical environment, it is not as intimidating as it allows users to experience figments of virtual elements without the vulnerability of being blind to the real world. In addition, AR can be experienced directly from head-up displays (HUDs) or handheld devices that users already own (e.g., tablet or mobile phones). Thus, AR is rapidly gaining prominence, and by 2024, the global AR market will be worth more than $165 billion (eMarketer 2017f). The recent introduction of Apple's ARKit and Google's ARCore, which allows independent developers to create their own AR applications, is expected to propel AR technology further into mainstream adoption.

3.2.2 Augmented Reality in Marketing

In a marketing context, AR has been used for three different purposes – to provide value as a core or peripheral product, to engage customers, or to enable product trial. Perhaps the most well-known application of this technology as an experiential product is Pokémon Go, a gaming app often credited for bringing AR to worldwide attention. Central to the playing experience is the AR technology, which superimposes animated creatures on a live view of players' surroundings, giving the illusion that these creatures coexist in the physical environment. AR can also be used as a peripheral product to enhance the consumption experience of other core products.

For example, Lego recently introduced an app that promises to bring their physical products to life and transform the entire playing experience. Using animated Lego characters designed to interact with physical Lego products, the app offers an entirely different experience from playing with the physical products alone. More recently, a Harvard Business Review article on AR (Porter and Heppelmann 2017) ingeniously incorporated the technology by directing readers to an app, which can be downloaded for free. When readers point the camera on their devices at specific pages in the article, they would be able to experience AR first-hand while learning about the technology. These cases illustrate how AR can create value by elevating the consumption experience.

AR’s ability to transform static objects into interactive and animated 3-dimensional objects offers new ways for marketers to create fresh experiences to captivate customers. In an excellent example of this application, Pepsi installed AR technology on a display wall at a bus shelter in London, transforming it into a fake window showing surrealistic but improbable scenarios such as flying saucers, a giant robot, and a tiger running wild in the city. The campaign was a huge success - videos of the campaign were widely viewed, and sales for Pepsi Max increased by 30 percent. AR can also be used to present information to people in engaging ways, as demonstrated by McDonald’s. Using an app, customers can discover the origins of various ingredients in their food via 3-dimensional animations that spring to life on tables. In these examples, the AR experience is incidental to the product being offered - absence of the technology would not diminish value derived from product consumption. However, AR is used to deliver interactive and memorable content, redefining the way brands or products are experienced.

The present research focuses on this latter application of AR as an instrument to facilitate purchase decisions. Specifically, I explore how virtual product experiences on AR influences customer engagement and purchase in field settings.

3.3 Research Framework

Research comparing AR-based product presentations with conventional websites showed that AR provides a more immersive search experience due to its enhanced interactivity (Yim et al. 2017). Consequently, customers found the experience more enjoyable, and perceived it to be more useful in facilitating purchase decisions. In line with this, Hilken et al. (2017) proposed that the value of AR over other online product presentation formats lies in its properties of environmental embedding and simulated physical control. That is, AR helps customers contextualize products in the environment they will be utilized in, and allows them to use natural bodily movements to control how products are presented. The unique combination of these two properties creates authentic and realistic product experiences, increasing customer's decision comfort (Hilken et al. 2017). These findings are consistent with prior research which found that vivid images and greater control over the presentation of product information are effective ways to reduce uncertainty in online purchases (Weathers et al. 2007). Furthermore, as the level of uncertainty or perceived risk of online purchase is reduced, customers have higher purchase intentions (Kim, Ferrin, and Rao 2009). Consistent with this, recent research has shown that the ability to assess product fit in online retail reduces purchase uncertainty and has a positive impact on sales (e.g., Bell et al 2018, Gallino and Moreno 2018). Taken together, I expect AR to positively impact customer engagement and purchase in online retail.

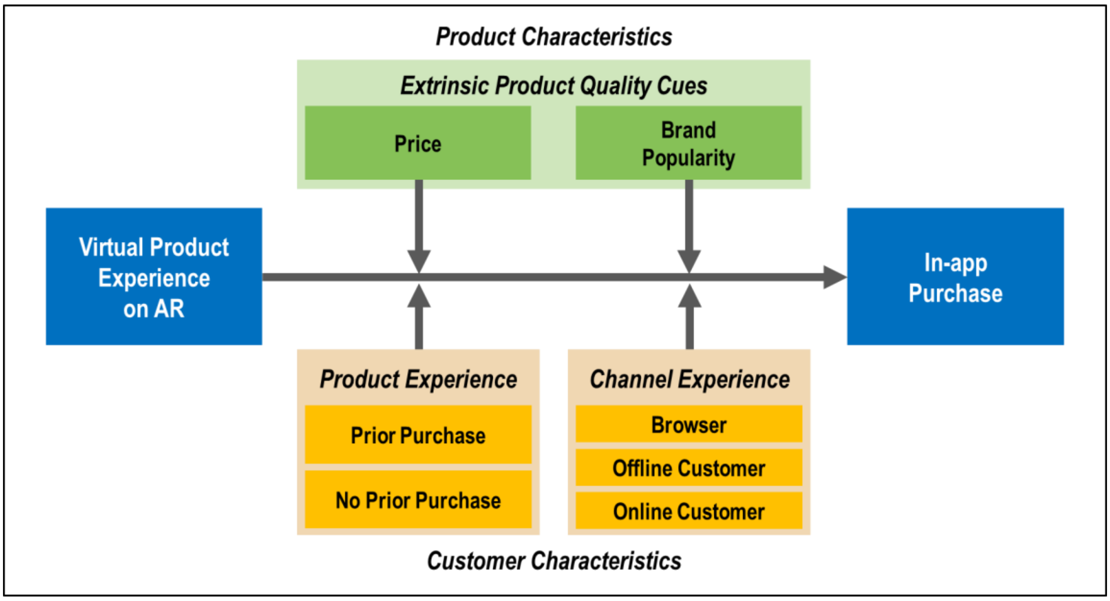
In addition, I am also interested to understand whether AR influences the importance of extrinsic cues such as price and brand popularity, promotes product exploration, and reduces barriers to purchasing online. In online environments, consumers often rely on extrinsic cues (e.g., product price and brand names; Dawar and Parker 1994, Rao and Monroe 1989) to infer product quality and make purchase decisions because they are not able to inspect products before purchasing (Danaher et al. 2003). Consistent with this, Tucker and Zhang (2011) found that popularity information on websites drove more page visits for products with narrower appeal because they were perceived to be stronger signals of quality. However, Chang and Wildt (1996) demonstrated that as the quantity and quality of intrinsic product information increase, consumers rely less on extrinsic cues. In the context of this research, if virtual product experiences via AR effectively communicates intrinsic product information, customers could rely less on extrinsic cues such as price and brand popularity in their purchase decisions. To examine if AR alters the importance of extrinsic cues in online purchase decisions, I consider how AR usage shifts customers' preferences towards cheaper products or less-popular brands.

Research has also found that in online environments, interactive media immerses users in a highly engaged state (i.e., flow), resulting in greater exploration (Hoffman and Novak 2009, Novak et al. 2000). Consistent with this, Zentner et al. (2013) provided evidence that customers' preferences shift to niche products as they move from offline to online channels. Customers are also more willing to engage in exploratory consumption when cost of experimentation is reduced (Datta et al. 2018). Since AR is a highly interactive medium and enables customers to try products effortlessly, I am interested to understand if AR increases product discovery, and whether this translates to preference for products or brands that customers have never purchased before. Thus, I also examine how customers' prior experience with products (or lack of it) influences the effect of AR on purchase.

In a recent paper, Bell et al. (2018) proposed that customers differ in their need to reduce product fit uncertainty before making a purchase, and demonstrated that offline showrooms (i.e., locations that let customers view and try physical products, but do not perform order fulfillment functions) attracts customers who have stronger need to sample products. Similarly, I expect customers' response to AR to differ based on their need to reduce product fit uncertainty. Customers who have purchased from the online retailer before (i.e., Online customers) may have a lesser need to assess product fit, as they are accustomed to making purchases in the absence of physical products. Consistent with this, Kim and Krishnan (2015) found that as online shopping experiences increase, customers are more inclined to purchase products with a higher degree of uncertainty. In contrast, customers who have made prior purchases at the retailer's offline channel, but have not purchased online before (i.e., Offline customers), may be deterred by the inability to assess product fit before making a purchase. Since AR simulates the in-store experience of trying products, it could be more effective in encouraging these customers to purchase online. Conversely, shoppers who have never purchased from a retailer before (i.e., Browsers) may still be hesitant to purchase due to their lack of familiarity with the retailer. To examine if customers from different channels respond differently to AR, I assess how the impact of AR varies based on customers' prior experience with retailers' channels.

To summarize, the present research explores AR's impact on customer engagement and purchase in online retail, and investigates how the effect of AR on purchase differ based on product price and brand popularity, as well as customers' prior product and channel experience. Figure 3.2 visually represents the framework for this research.

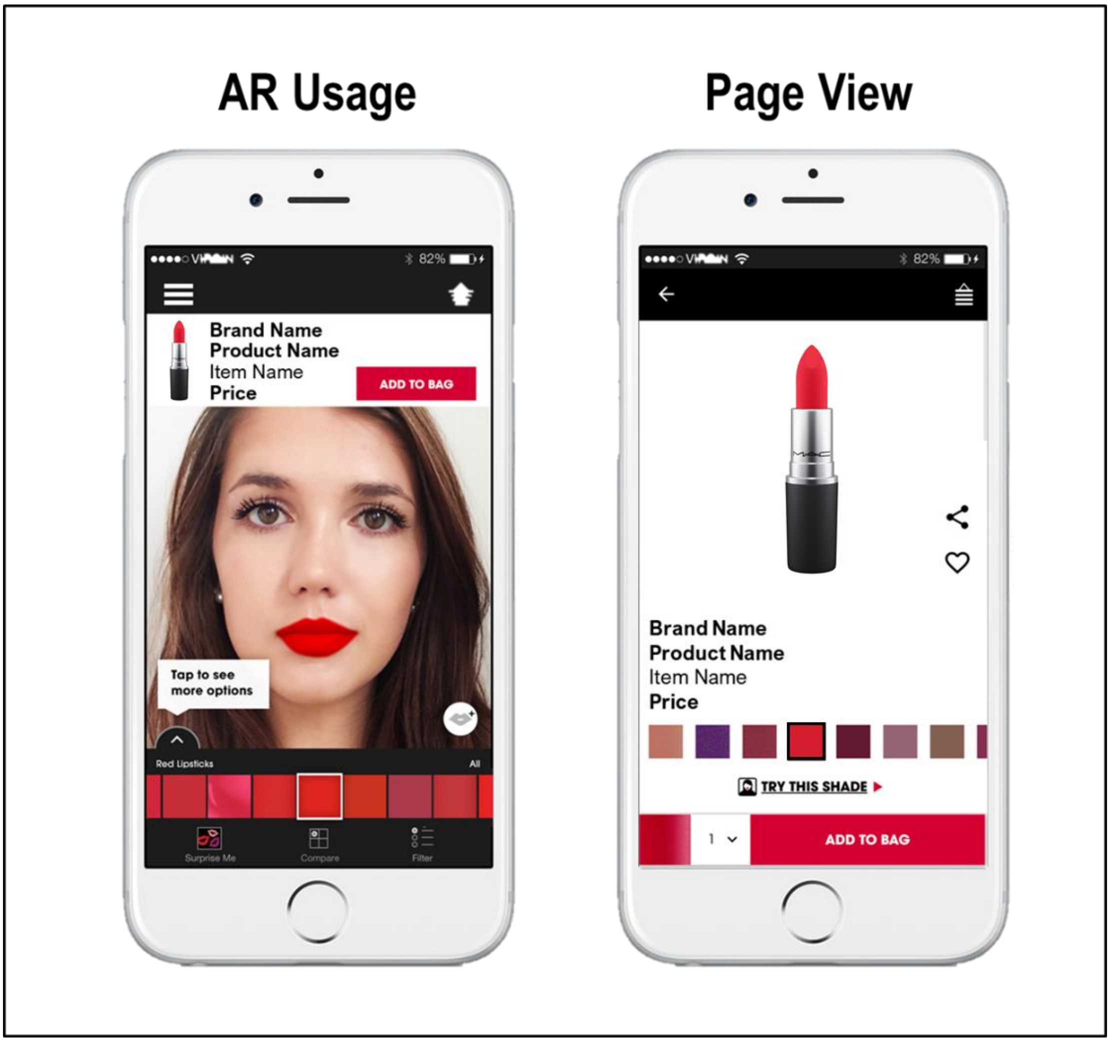
Figure 3.2 Research Framework



3.4 Methodology

As AR is predominantly available on mobile apps, my research centers on AR usage on the mobile app platform. I obtained app activity data from an international cosmetics retailer (having both online and offline presence). Leveraging AR technology, the retailer integrated a new feature on their existing mobile app that allows customers to virtually try on make-up products (e.g., lipsticks, eye liner). The AR technology identifies customers' facial features via smartphone cameras, and super-imposes the color of chosen products onto a live view of customers' face in real-time. Information on the brand, product, and variant name for the selected product is provided at the top of the screen. The left image in Figure 3.3 provides an example of a customer trying on the AR feature. For comparison, the right image shows an example of the product pageview, which is the conventional way of conveying product-related information on mobile retail apps.

Figure 3.3 Example of Product Exposure on Mobile App

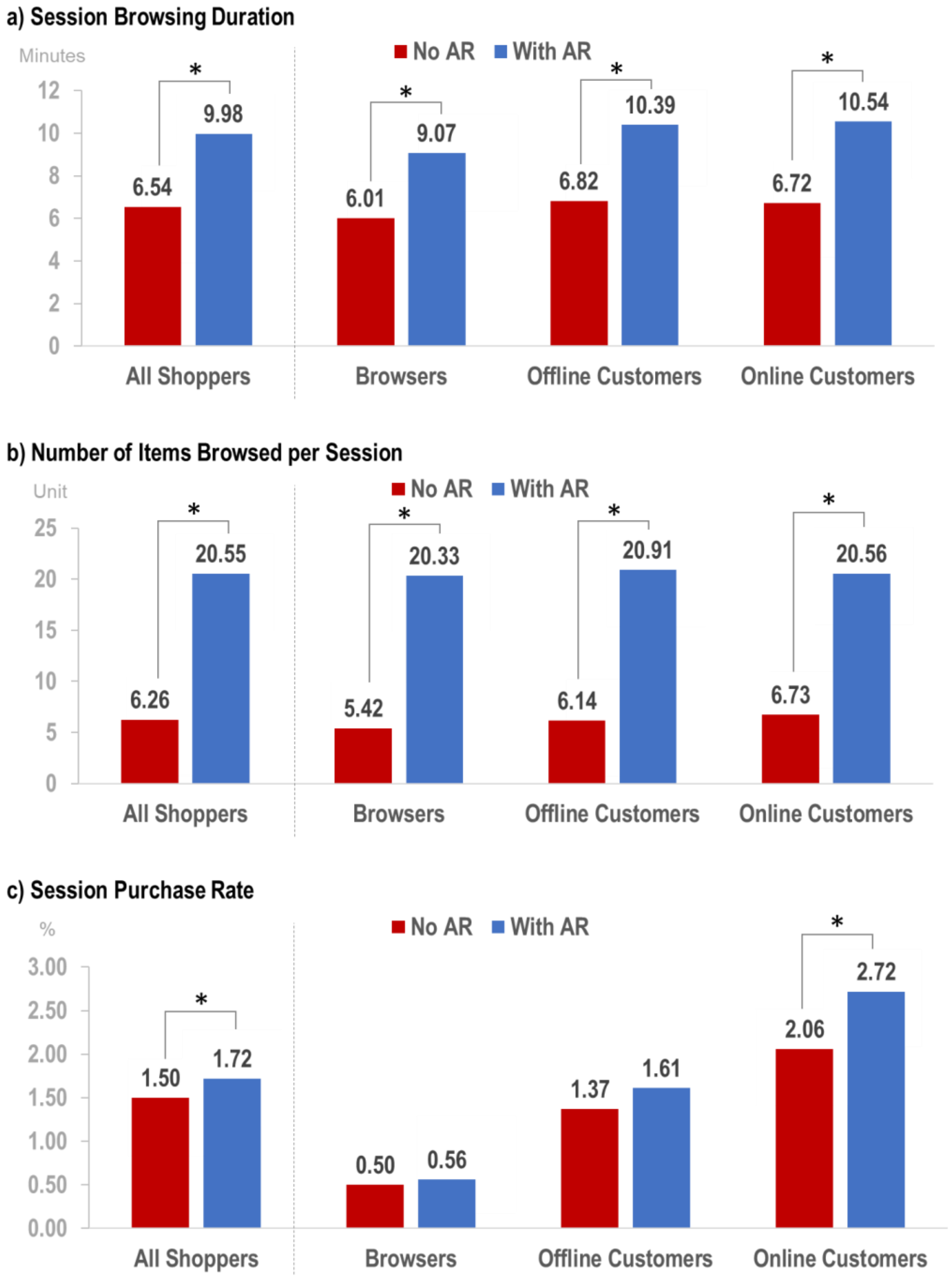


The dataset covers an 8-month period from December 2017 to August 2018, and contains information on exposures to product page, usage of the AR feature, and in-app purchases. Using customers' loyalty card number, I merged this dataset with the retailer's online and offline transaction data to construct comprehensive purchase histories for each customer. Before elaborating on the empirical model, which is performed at the customer-session-product-level to incorporate product-related characteristics, I will first provide an overview of AR usage behavior at the customer and session-level.

During the period of observation, 147,272 shoppers visited the retailer's mobile app. Of these shoppers, 24.7% made prior online purchases with the retailer (i.e., Online customers), 17.2% only purchased from the retailer's offline channel (i.e., Offline customers), and the remaining 58.1% of shoppers never purchased from the retailer before (i.e., Browsers). Compared to Online customers, Offline customers and Browsers were less likely to use the AR feature during the period of observation (14.3% and 8.8% vs 15.1% for Online customers, $p < .01$ for both). Nevertheless, among those who used AR, Offline customers and Browsers spent more time on the feature (2.41 minutes and 2.58 minutes vs 2.23 minutes for Online customers, $p < .01$ for both), and tried more items (11.48 and 12.88 vs 10.12 for Online customers, $p < .01$ for both).

Over the 8-month period, the shoppers initiated 783,784 browsing sessions on the mobile app. Figure 3.4 compares the browsing duration, number of products viewed, and purchase rate between sessions with AR usage and sessions without AR usage for different customer segments. Across all segments, customers spend 52.6% more time on the mobile app (Figure 3.4a), and view 3.3 times more products (Figure 3.4b) during sessions which involved AR usage. Customers are also significantly more likely to make a purchase when they use AR during the session (Figure 3.4c), though this increase mainly comes from Online customers.

Figure 3.4 Session-level Browsing Activity and Purchase Rate by AR Usage



** Significant at p < .01 level*

	All Shoppers	Browsers	Offline Customers	Online Customer
Definition	All app visitors	Shoppers with no purchase history	Shoppers who have only purchased from physical stores	Shoppers who have made at least one online purchase
Total Session Observations	783,784	220,654	144,780	418,350
Sessions with No AR usage	752,758	209,509	138,741	404,508
Sessions with AR usage	31,026	11,145	6,039	13,842

To examine how the effect of AR differs by product characteristics, I estimated the model at the customer-session-product-level. Due to the time taken to adapt the technology for different facial features, the AR function was introduced at different times for different product categories, providing a natural experiment for the research. I took advantage of this unique setting to account for customers' self-selection in usage of the AR feature, which will be explained in the next section. The feature was available for lips products for at least a year before the start of the observation period, minimizing the possibility that the effects I find are due to novelty. At the end of March 2018, the feature was introduced for eyes products. The AR feature was not available for every item[2] within each category due to logistical reasons. To minimize bias arising from availability of AR feature, I focused on categories where the AR feature is available for more than 90% of items in my analysis[3]. These categories are lipstick, lip gloss, and eye liner, and the percentage of items with AR feature are 98%, 93%, and 92% respectively.

In total, there are 2,830 unique items in the dataset. Figure 3.5 summarizes availability of the AR feature for these categories from Dec 2017 to Aug 2018. During the study period, 63,555 customers were exposed to lipstick, lip gloss, and eye liner products on the mobile app across 195,617 sessions, giving 1,515,093 observations, with 19.2% involving usage of the AR feature.

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[2] I consider each shade / color of a cosmetic product as a unique item. This level of granularity is important, since product color is an important determinant of purchase in this research context.

[3] Analysis was replicated for all categories with products on AR, and findings are generally consistent. Output for this model is provided in the results section.

Figure 3.5 Availability of AR Feature by Product Category

<table>
<tr><th></th><th>LIPSTICK</th><th>LIP GLOSS</th><th>EYE LINER</th><th>TOTAL</th></tr>
<tr><td>Total number of items (brands) in category</td><td>1,966 items (39 brands)</td><td>342 items (27 brands)</td><td>522 items (36 brands)</td><td>2,830 items (46 brands)</td></tr>
<tr><td>Dec 2017 - Mar 2018</td><td rowspan="2">1,918 items (38 brands)</td><td rowspan="2">319 items (26 brands)</td><td>AR not available</td><td>2,237 items (39 brands)</td></tr>
<tr><td>Apr 2018 - Aug 2018</td><td>479 items (34 brands)</td><td>2,716 items (44 brands)</td></tr>
</table>

Note: each shade / color of a cosmetic product is considered a unique item.

3.5 Empirical Model

3.5.1 Accounting for Self-Selection in AR Usage

My main interest is on how usage of the AR feature influences the probability of customer i buying item j during session t, $P(Buy_{ijt})$. However, the decision to use the feature is determined by customers, which introduces self-selection bias. For example, customers who are already inclined to purchase an item may be more likely to try it using the AR feature. To account for self-selection bias, I use the control function approach (Petrin and Train 2010), which controls for the portion of the dependent variable that would otherwise correlate with unobserved variables arising from self-selection. I first estimate the probability of customer i using the AR feature for item j during session t, $P(ARusage_{ijt})$, using a probit model. Residuals from this first stage are then included to estimate $P(Buy_{ijt})$ in the second stage.

To ensure that the model is identified, I included two instruments that predict usage of the AR feature, but is not directly related to customers' purchase decision, in the first stage estimation. As the AR feature was introduced at different times for different products categories, I used the availability of AR feature for item j during session t, $ARavailability_{jt}$, as the first instrument to control for selection bias at the customer-level. This variable is coded as a 1 if the AR feature was available for product j at time t, and 0 otherwise. Since customers are unable to use the feature for a particular item before it is available, AR availability has a direct impact on its usage. Furthermore, the decision of when to introduce the feature for different products categories was made by the retailer, and was contingent on time taken to adapt the technology. Thus, availability of the AR feature does not have a direct relationship with customers' decision to purchase a specific item, satisfying the exclusion requirement.

The second instrument, $PriorARusage_{it}$, is an indicator variable representing customers' prior usage of the AR feature for other products besides item j, and controls for selection bias at the item-level. It is coded as a 1 if customer i used the AR feature to try any product other than item j before session t, and 0 otherwise. Since the AR feature was not advertised and is not prominent, customers who have not used the feature prior to session t may be unaware of it, and likelihood of using the feature on item j during session t should be low. Conversely, customers who have used the feature on other products should have a higher likelihood of using it again for item j. Furthermore, prior experience with the AR feature for other products should not be directly related to the probability of purchasing item j, satisfying the exclusion restriction. As a more stringent instrument, I also used prior usage of the AR feature for products in other categories (besides the category of item j) as an alternative measure. The output is consistent with the main model, and are presented in the results section.

3.5.2 Model Specification

Using these two instruments, I first estimated P($ARusage_{ijt}$) with the following equation:

$$
(1)\ P\left(ARusage_{ijt} = 1 \middle| X\right) = \Phi\big(\gamma_0 + \gamma_1 ARavailability_{jt} + \gamma_2 PriorARusage_{it} + \gamma_3 Price_{jt} + \gamma_4 BrandPopularity_{jt} + \gamma_5 NewtoCategory_{ijt} + \gamma_6 NewtoBrand_{ijt} + \gamma_7 NewtoItem_{ijt} + \gamma_8 Browser_{it} + \gamma_9 Offline_{it} + \gamma_{10} Browsing_{ijt} + \gamma_{11} Customer_{it} + \gamma_{12} Item_{jt}\big)
$$

Table 3.1 provides a summary of how the variables are operationalized. In equation (1), $ARusage_{ijt}$ is a binary variable indicating if customer i tried product j using the AR feature during session t. $ARavailability_{jt}$ represents the first instrument, and $PriorARusage_{it}$ refers to the second instrument. $Price_{jt,}$ is the retail price of item j, and $BrandPopularity_{jt}$ is operationalized as the past one month share of sales of item j's brand in the category (e.g., share of sales of Brand A lipstick among all lipsticks). I included three indicator variables to capture customers' prior experience (or lack thereof) with item j. Customers who have previously purchased item j serve as the base level. $NewtoCategory_{ijt}$ represents customers who have never purchased a product from the same category as item j prior to session t; $NewtoBrand_{ijt}$ represents customers who have purchased a product from the same category, but not the same brand, as item j; $NewtoItem_{ijt}$ represents customers who purchased a product from the same brand and category as item j, but not item j. To represent customers' prior experience with the retailer, I used customers who have made prior online purchases with the retailer as the base level, and included two indicator variables, $Browser_{it}$ and

Offline_{it}, to represent customers who have not made any purchases with the retailer, and customers who have only made prior offline purchases, respectively.

Table 3.1 Variable Operationalization

Variables	Operationalization	In First Stage	In Second Stage
Variables of Interest			
AR Usage (1/0)	1 if customer i used AR to try item j during session t; 0 otherwise	No	Yes
Price	Retail price for item j	Yes	Yes
Brand Popularity	Past 1 month sales of brand in the category / Past 1 month category sales	Yes	Yes
New to Category (1/0)	1 if customer i have never purchased products in the category before session t; 0 otherwise	Yes	Yes
New to Brand (1/0)	1 if customer i purchased products in the category, but have never purchased the brand in the category before session t; 0 otherwise	Yes	Yes
New to Item (1/0)	1 if customer i purchased the brand in the category, but have never purchased item j before session t; 0 otherwise	Yes	Yes
Browser (1/0)	1 if customer i have no prior purchase with the retailer before session t; 0 otherwise	Yes	Yes
Offline (1/0)	1 if customer i have no prior online purchase with the retailer, but made at least 1 offline purchase before session t; 0 otherwise	Yes	Yes
Instruments			
AR Availability (1/0)	1 if AR feature is available for item j during session t; 0 otherwise	Yes	No
Prior AR Usage (1/0)	1 if customer i used AR feature for any products other than item j prior to session t; 0 otherwise	Yes	No

Table 3.1 Variable Operationalization (continued)

Variables	Operationalization	In First Stage	In Second Stage
Control Variables			
Browsing Duration	Log of browsing duration (minutes) during session t	Yes	Yes
No. of Items Browsed	Number of items tried on AR or viewed during session t		
Same-day Item Trial (1/0)	1 if customer i used AR to try item j on the same day prior to session t; 0 otherwise	Yes	Yes
Same-day Item View (1/0)	1 if customer i viewed product page for item j on the same day prior to session t; 0 otherwise	Yes	Yes
Days from First Order	Number of days from customer i's first order with the retailer; 0 for Browsers		
No. of Previous Orders	Number of previous transactions with retailer; 0 for Browsers	Yes	Yes
Average Order Value	Total value of all transactions with retailer / Number of previous transactions with retailer; 0 for Browsers	Yes	Yes
Past 1 Month Item Sales	Past 1 month sales of item j	Yes	Yes

Additionally, I included a vector of covariates to control for browsing, customer, and item-related effects. $Browsing_{ijt}$ includes browsing duration and number of items browsed during session t, as well as variables to indicate if customer i tried item j on AR or viewed its product page on the same day prior to session t. $Customer_{it}$ controls for customers' relationship with the retailer at time t, including days from first order, number of previous orders, and average order value. Lastly, $Item_{jt}$ contains brand and category fixed effects, and past one month share of sales of item j. All continuous variables in the model are mean-centered and standardized to facilitate comparison of effects. Table 3.2 provides descriptive statistics for these variables, and the correlations are displayed in Table 3.3.

Table 3.2 Descriptive Statistics

	Mean	**SD**	**Min**	**Median**	**Max**
1. AR Usage (1/0)	.19	.39	.00	.00	1.00
2. Price	27.13	9.46	5.00	28.30	75.30
3. Brand Popularity	.13	.16	.00	.07	.59
4. New to Category (1/0)	.49	.50	.00	.00	1.00
5. New to Brand (1/0)	.34	.47	.00	.00	1.00
6. New to Item (1/0)	.16	.37	.00	.00	1.00
7. Browser (1/0)	.27	.44	.00	.00	1.00
8. Offline (1/0)	.18	.39	.00	.00	1.00
9. AR Availability (1/0)	.95	.22	.00	1.00	1.00
10.Prior AR Usage (1/0)	.21	.41	.00	.00	1.00
11.Browsing Duration (mins)	15.35	13.53	.00	11.04	58.01
12.No. of Items Browsed	35.25	33.55	1.00	25.00	386.00
13.Same-day Item Trial (1/0)	.00	.06	.00	.00	1.00
14.Same-day Item View (1/0)	.02	.14	.00	.00	1.00
15.Days from First Order	775.90	759.28	.00	547.00	2,268.00
16.No. of Previous Orders	11.68	13.08	.00	7.00	62.00
17.Average Order Value	60.42	52.83	.00	59.86	1,981.00
18.Past 1 Month Item Sales	328.80	974.07	.00	43.00	16,410.00

Table 3.3 Correlations Table

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1. AR Usage (1/0)	1.00																	
2. Price	.06	1.00																
3. Brand Popularity	-.06	-.66	1.00															
4. New to Category (1/0)	.12	-.04	.03	1.00														
5. New to Brand (1/0)	-.05	.13	-.15	-.69	1.00													
6. New to Item (1/0)	-.09	-.11	.14	-.43	-.32	1.00												
7. Browser (1/0)	.13	-.04	.04	.62	-.43	-.27	1.00											
8. Offline (1/0)	.02	-.01	.01	-.08	.07	.02	-.28	1.00										
9. AR Availability (1/0)	.11	.07	-.04	-.05	.04	.02	.03	.01	1.00									
10. Prior AR Usage (1/0)	.33	-.01	.01	-.02	.01	.01	-.03	.00	.04	1.00								
11. Browsing Duration	.03	.00	-.02	.01	.01	-.02	-.03	.01	-.03	.00	1.00							
12. No. of Items Browsed	.25	.03	-.02	.02	.00	-.02	.03	.00	.07	.09	.44	1.00						
13. Same-day Item Trial (1/0)	.10	.00	.00	.01	.00	-.01	.01	.00	.01	.12	-.02	-.01	1.00					
14. Same-day Item View (1/0)	-.03	.00	.01	-.02	.00	.02	-.02	.00	.00	.02	-.04	-.05	.13	1.00				
15. Days from First Order	-.09	.06	-.04	-.53	.35	.25	-.61	.09	-.02	.00	.02	-.02	-.01	.01	1.00			
16. No. of Previous Orders	-.12	.07	-.05	-.58	.36	.29	-.54	-.04	-.02	-.01	-.01	-.03	-.02	.01	.71	1.00		
17. Average Order Value	.01	.02	-.02	-.01	.02	.00	-.01	-.01	.00	.01	.01	.01	.00	.00	.00	.00	1.00	
18. Past 1 Month Item Sales	-.04	-.05	.21	.01	-.02	-.02	.00	.01	.01	-.02	-.07	-.12	.00	.02	.00	.00	.00	1.00

I included the estimated residuals from (1) into the estimation of P(Buy_{ijt}) in the second stage. The equation is given by:

$$
\begin{aligned}
(2)\ P\left(Buy_{ijt} = 1 \middle| X\right) \\
&= \Phi\big(\beta_0 + \beta_1 ARusage_{ijt} + \beta_2 Price_{jt} + \beta_3 BrandPopularity_{jt} \\
&+ \beta_4 NewtoCategory_{ijt} + \beta_5 NewtoBrand_{ijt} + \beta_6 NewtoItem_{ijt} \\
&+ \beta_7 Browser_{it} + \beta_8 Offline_{it} + \beta_9 ARusage \times Price_{jt} \\
&+ \beta_{10} ARusage \times BrandPopularity_{jt} \\
&+ \beta_{11} ARusage \times NewtoCategory_{ijt} \\
&+ \beta_{12} ARusage \times NewtoBrand_{ijt} + \beta_{13} ARusage \times NewtoItem_{ijt} \\
&+ \beta_{14} ARusage \times Browser_{jt} + \beta_{15} ARusage \times Offline_{jt} \\
&+ \beta_{16} Browsing_{ijt} + \beta_{17} Customer_{it} + \beta_{18} Item_{jt} + \lambda\mu_{ijt}\big)
\end{aligned}
$$

There are three key differences between equation (2) and (1). Firstly, the instruments, $ARavailability_{jt}$ and $PriorARusage_{it}$, are excluded from (2). Secondly, I included $ARusage_{ijt}$, the endogenous regressor, and $\lambda\mu_{ijt}$, the control function to correct for selection bias. Thirdly, I included interactions between $ARusage_{ijt}$ and variables of interest, namely $Price_{jt}$, $BrandPopularity_{jt}$, $NewtoCategory_{ijt}$, $NewtoBrand_{ijt}$, $NewtoItem_{ijt}$, $Browser_{it,}$ and $Offline_{it}$.

As the estimate of μ_{ijt}, rather than the true μ_{ijt}, is used in the second-stage estimation, the asymptotic sampling variance in the second stage needs to account for this additional source of variance (Petrin and Train 2010). Following Petrin and Train's (2010) suggestion, the standard errors were corrected using standard formulas from two-step estimators. In particular, I used the two-stage standard error formula derived by Terza (2016). Furthermore, to allow correlations among items tried during the session, standard errors for both equations were clustered at the session-level.

3.6 Results

3.6.1 Main Results

Results from the first and second stage are presented in Table 3.4. The coefficients for the first stage of estimation are displayed in the first column of Table 3.4, and represent customer and product characteristics affecting the decision to try an item on AR. The results suggest that customers are more likely to use AR to try less-popular brands (-.217, $p < .05$). Furthermore, they are also more likely to use AR for categories, brands or items they have not purchased before (.482, .311, and .122 respectively, $p < .05$ for all). Compared to Online customers (i.e., base level), Browsers and Offline customers are more likely to use AR (.406 and .261 respectively, $p < .05$ for all). Lastly, the coefficients for AR Availability (2.208, $p < .05$) and Prior AR Usage (1.029, $p < .05$) are both positive and highly significant, demonstrating that these two exclusion restrictions are strong predictors of the probability of using the AR feature.

The coefficients for the second stage of estimation are given in the second column of Table 3.4. The coefficient for the residual correction term is significant (.366, $p < .05$), highlighting the importance of correcting for endogeneity. Since I included interactions between AR Usage and indicator variables representing customers' prior experience with the product (i.e., New to Category, Brand, or Item) and retailer (i.e., Browsers and Offline), the coefficient for AR Usage is interpreted with respect to the base level – customers with prior online purchases who used AR to view items that they have purchased before. The coefficient for AR Usage is significantly negative (-.698, $p < .05$), indicating that online customers are less likely to purchase items they have purchased before if they use the AR feature to try these items.

Table 3.4 Model Estimation Results

	First Stage	**Second Stage**
Response Variable	$P(ARusage)_{ijt}$	$P(Buy)_{ijt}$
Variables of Interest		
AR Usage		**-.698** (.194)
Price	-.014 (.009)	.009 (.018)
Brand Popularity	**-.217** (.014)	-.027 (.019)
New to Category	**.482** (.025)	**-.553** (.034)
New to Brand	**.311** (.023)	**-.496** (.031)
New to Item	**.122** (.018)	**-.444** (.032)
Browsers	**.406** (.020)	**-.243** (.032)
Offline	**.261** (.017)	**-.091** (.024)
Interactions		
AR Usage × Price		**-.078** (.032)
AR Usage × Brand Popularity		**-.130** (.035)
AR Usage × New to Category		**.458** (.189)
AR Usage × New to Brand		**.420** (.186)
AR Usage × New to Item		**.512** (.185)
AR Usage × Browsers		.011 (.076)
AR Usage × Offline		-.078 (.064)
Endogeneity Correction		
Instrument 1: AR Availability	**2.208** (.053)	
Instrument 2: Prior AR Usage	**1.029** (.013)	
Correction Term		**.366** (.069)
Other Variables		
Browsing Duration	**-.111** (.006)	**.293** (.010)
No. of Items Browsed	**.367** (.010)	**-.372** (.022)
Same-day Item Trial	**1.348** (.053)	.026 (.085)
Same-day Item View	**-.623** (.034)	**.554** (.029)
Days from First Order	**.086** (.010)	**.052** (.011)
No. of Previous Orders	**-.088** (.011)	-.011 (.011)
Mean Order Value	.002 (.002)	**.006** (.002)
Past 1 Month Item Sales	**.008** (.003)	**.074** (.004)
Brand fixed effects	Included	Included
Category fixed effects	Included	Included
Constant	**-3.979** (.064)	**-2.130** (.054)
Observations	1,515,093	1,515,093
Log Likelihood	-564,195	-19,710

Note: Robust standard errors are in parentheses; statistically significant estimates ($p < .05$) are in bold.

The coefficients for the interaction between AR Usage and Price as well as Brand Popularity are significantly negative (-.078 and -.130 respectively, $p < .05$ for both), indicating that the effect of AR usage on purchase is stronger for products that are less expensive, and brands that are less popular. The interaction between New to Category, New to Brand, and New to Item variables and AR Usage are positive and significant (.458, .420, and .512 respectively, $p < .05$ for all), indicating that customers have a higher likelihood of purchasing product categories, brands, and items they have never purchased before after trying it on AR. The coefficients for Browsers and Offline customers are significantly negative (-.243 and -.091 respectively, $p < .05$ for both), while their interactions with AR Usage are not significant. This result suggests that while Browsers and Offline customers are less likely to purchase compared to Online customers, contrary to expectations, the effect of AR usage on purchase does not differ by customers' prior experience with the retailer.

To summarize my findings, customers who use AR spend more time on the mobile app and browse more products, suggesting higher levels of engagement with the app. At the product level, I find that AR has a stronger impact for cheaper products and less popular brands, suggesting that price and brand popularity become less important as extrinsic quality cues when customers are able to try products virtually to determine product fit. Furthermore, AR is effective in encouraging customers to explore categories, brands, or items they have never purchased before. Contrary to expectations, the influence of AR did not differ by customers' prior experience with the retailer's channel.

3.6.2 Robustness Checks

To ensure that the findings are robust, I repeated the analysis using alternative estimation method, model specification, variable and instrument operationalization, and sample definition. The outputs for these models are consistent with the main model, and the coefficients are presented in Table 3.5 and Table 3.6.

The main model is presented in column (1) of both tables for comparison. Column (2) in Table 3.5 contains the model without endogeneity correction. Though the magnitude of the coefficients are slightly different, the direction and significance of the effects are consistent with the main model.

Column (3) in Table 3.5 contains the model estimated using the Heckman selection method (Heckman 1979), which allows errors in a first-stage selection equation (i.e., decision to use the AR feature to try item j) to correlate with errors in a second-stage outcome equation (i.e., decision to buy item j) following a bivariate normal distribution. Instead of using the residuals from the first stage as a control function, I derive the inverse Mills ratio (IMR) and include it in the second stage to estimate $P(Buy)_{ijt}$ in the outcome equation. This method was previously used by Gill et al. (2017) in a similar research context to account for self-selection in the adoption of a business-to-business mobile app. Since this method is more suited for continuous response variable, I used the control function approach in the main model, but would also like to note that the coefficient magnitude, direction, and significance are consistent for both estimation approaches.

In the model reported in Column (4) in Table 3.5, I allow the errors among products viewed by the same customer across sessions to correlate by clustering the standard errors at the customer-level instead of session-level.

Table 3.5 Robustness Checks

	(1) Main Model	(2) Model Without Correction	(3) Estimation using Heckman Approach	(4) Standard Errors Clustered at Customer-level	(5) AR Usage for Other Categories as Instrument
Variables of Interest					
AR Usage	**-.698** (.194)	**-.436** (.179)	**-.754** (.207)	**-.698** (.195)	**-.731** (.196)
Price	.009 (.018)	.009 (.018)	.008 (.018)	.009 (.018)	.009 (.018)
Brand Popularity	-.027 (.019)	-.030 (.019)	-.038 (.020)	-.027 (.020)	-.027 (.019)
New to Category	**-.553** (.034)	**-.548** (.034)	**-.537** (.035)	**-.553** (.036)	**-.554** (.034)
New to Brand	**-.496** (.031)	**-.493** (.031)	**-.488** (.031)	**-.496** (.033)	**-.496** (.031)
New to Item	**-.444** (.032)	**-.443** (.032)	**-.443** (.032)	**-.444** (.034)	**-.444** (.032)
Browsers	**-.243** (.032)	**-.235** (.032)	**-.219** (.032)	**-.243** (.032)	**-.243** (.032)
Offline	**-.091** (.024)	**-.087** (.024)	**-.078** (.024)	**-.091** (.025)	**-.091** (.024)
Interactions					
AR Usage × Price	**-.078** (.032)	**-.083** (.032)	**-.082** (.032)	**-.078** (.032)	**-.078** (.032)
AR Usage × Brand Popularity	**-.130** (.035)	**-.108** (.034)	**-.122** (.035)	**-.130** (.035)	**-.130** (.035)
AR Usage × New to Category	**.458** (.189)	**.405** (.184)	**.447** (.188)	**.458** (.189)	**.461** (.189)
AR Usage × New to Brand	**.420** (.186)	**.384** (.182)	**.416** (.186)	**.420** (.187)	**.414** (.186)
AR Usage × New to Item	**.512** (.185)	**.493** (.182)	**.515** (.185)	**.512** (.185)	**.504** (.185)
AR Usage × Browsers	.011 (.076)	-.023 (.074)	-.010 (.075)	.011 (.076)	.018 (.076)
AR Usage × Offline	-.078 (.064)	-.104 (.064)	-.091 (.065)	-.078 (.065)	-.073 (.065)
Other Variables					
Correction Term	**.366** (.069)	-	**.165** (.044)	**.366** (.069)	**.396** (.071)
Brand / category fixed effects	Included	Included	Included	Included	Included
Constant	**-2.130** (.054)	**-2.124** (.055)	**-2.104** (.054)	**-2.130** (.057)	**-2.129** (.054)
Observations	1,515,093	1,515,093	1,515,093	1,515,093	1,515,093
Log Likelihood	-19,710	-19,728	-19,714	-19,710	-19,710

Note: Robust standard errors are in parentheses; estimates that are statistically significant ($p < .05$) are in bold.

Table 3.6 Robustness Checks

	(1) **Main Model**	**(2)** **Excluding Brand Fixed Effects**	**(3)** **Absolute Sales for Brand Popularity**	**(4)** **Same-day Purchase as Response Variable**	**(5)** **All Product Categories**
Variables of Interest					
AR Usage	**-.698** (.194)	**-.643** (.197)	**-.725** (.198)	**-.678** (.177)	**-.681** (.193)
Price	.009 (.018)	-.016 (.010)	.011 (.018)	.009 (.017)	.007 (.014)
Brand Popularity	-.027 (.019)	.007 (.011)	-.017 (.017)	-.020 (.018)	.007 (.013)
New to Category	**-.553** (.034)	**-.526** (.034)	**-.554** (.034)	**-.543** (.033)	**-.478** (.029)
New to Brand	**-.496** (.031)	**-.457** (.031)	**-.500** (.031)	**-.486** (.030)	**-.447** (.028)
New to Item	**-.444** (.032)	**-.441** (.032)	**-.449** (.032)	**-.432** (.031)	**-.398** (.029)
Browsers	**-.243** (.032)	**-.234** (.032)	**-.244** (.032)	**-.252** (.030)	**-.272** (.026)
Offline	**-.091** (.024)	**-.090** (.024)	**-.091** (.024)	**-.088** (.023)	**-.096** (.020)
Interactions					
AR Usage × Price	**-.078** (.032)	**-.069** (.031)	**-.064** (.030)	**-.078** (.030)	**-.131** (.058)
AR Usage × Brand Popularity	**-.130** (.035)	**-.108** (.033)	**-.124** (.040)	**-.150** (.033)	**-.116** (.032)
AR Usage × New to Category	**.458** (.189)	**.450** (.186)	**.471** (.192)	**.406** (.174)	**.401** (.186)
AR Usage × New to Brand	**.420** (.186)	**.406** (.183)	**.461** (.189)	**.380** (.171)	**.391** (.185)
AR Usage × New to Item	**.512** (.185)	**.501** (.183)	**.557** (.189)	**.453** (.171)	**.472** (.184)
AR Usage × Browsers	.011 (.076)	.002 (.075)	.022 (.077)	.026 (.071)	.041 (.072)
AR Usage × Offline	-.078 (.064)	-.084 (.064)	-.079 (.065)	-.045 (.059)	-.071 (.062)
Other Variables					
Correction Term	**.366** (.069)	**.296** (.093)	**.354** (.069)	**.386** (.064)	**.341** (.072)
Brand / category fixed effects	Included	Category only	Included	Included	Included
Constant	**-2.130** (.054)	**-2.309** (.037)	**-2.180** (.051)	**-2.103** (.052)	**-2.536** (.048)
Observations	1,515,093	1,515,093	1,515,093	1,515,093	1,923,373
Log Likelihood	-19,710	-19,837	-19,712	-22,320	-26,719

Notes: Robust standard errors are in parentheses; estimates that are statistically significant ($p < .05$) are in bold.

Additionally, one of the instrument in the first stage was customers' prior usage of AR to try other items besides item j. The justification for this instrument is that customers who are aware of the feature, and have used it for other items, are more likely to use it for item j, but usage of the feature for other items should not influence purchase for item j. As a more stringent measure, I substituted this with another variable to represent customers' prior usage of AR to try other product that are not in the same category as item j. Results for the second stage estimation using this alternative instrument is presented in column (5) of Table 3.5.

In the main model, brand popularity was operationalized as share of brand sales within a category in the past one month. However, due to the inclusion of brand fixed effects, the estimated coefficient represents changes in brand-share levels within a brand, rather than between brands. To see if the results hold when popularity between brands are compared, I estimated the model without brand fixed effects and present this result in column (2) of Table 3.6. Furthermore, share of brand sales could be inflated if there are few brands in the category. Thus, I estimated the same model using absolute brand sales in the category in the past one month (controlling for absolute category sales). The output is presented in column (3) of Table 3.6.

As customers may make purchase decisions across multiple browsing sessions on the app, I used same-day purchases as an alternative response variable instead of purchases within the same session. Thus, the response variable is the probability of customer i purchasing item j on a day t, given that the customer tried the item on AR earlier in the day. Results for this model is given in column (4) of Table 3.6.

Finally, the main model focused on categories where more than 90% of the items are available on AR to minimize selection bias at the product-level arising from availability of AR. I replicated the estimation by including all product categories that have items with the AR feature. The results are reported in column (5) of Table 3.6.

To summarize, across multiple robustness checks, the direction, magnitude, and significance of coefficients are highly consistent with the main model, suggesting that the findings are robust.

3.6.3 Additional Analyses

The sample used in the main model includes observations of product exposures through product page views or usage of the AR feature (non-mutually exclusive). To assess the incremental effect of using AR beyond providing product exposures, I excluded customers who were exposed to products only via the AR feature. Thus, all customers in this alternate sample were exposed to products via the page view, and the AR Usage variable now captures the incremental impact of trying products on AR. The coefficients for this model, presented in column (2) of Table 3.7, suggest that AR provides incremental value over merely providing product exposure.

To assess if the effects observed is due to novelty of the AR feature, I included FirstARusage, an indicator variable to represent customers who are using the feature for the first time, as a covariate and interacted it with ARusage. If novelty effects exist, the effect of AR usage on purchase should be stronger among customers who are using the feature for the first time, and the interaction term should be significantly positive. Results for this alternative model is presented in column (3) in Table 3.7. I find that the direction, magnitude, and significance of the effects are consistent with the main model. Importantly, the interaction between ARusage and FirstARusage is not significant, suggesting that the impact of AR usage on purchase does not significantly differ between customers who are using the AR feature for the first time, and those who have used the feature before.

Table 3.7 Additional Analyses

	(1) Main Model	(2) Incremental Effect	(3) Novelty Effect
Variables of Interest			
AR Usage	**-.698** (.194)	**-.955** (.252)	**-.693** (.197)
Price	.009 (.018)	.009 (.018)	.009 (.018)
Brand Popularity	-.027 (.019)	-.033 (.020)	-.025 (.019)
New to Category	**-.553** (.034)	**-.546** (.034)	**-.557** (.034)
New to Brand	**-.496** (.031)	**-.493** (.031)	**-.499** (.031)
New to Item	**-.444** (.032)	**-.443** (.032)	**-.445** (.032)
Browsers	**-.243** (.032)	**-.235** (.032)	**-.249** (.032)
Offline	**-.091** (.024)	**-.087** (.024)	**-.094** (.024)
First AR Usage	-	-	**.078** (.027)
Interactions			
AR Usage × Price	**-.078** (.032)	**-.090** (.040)	**-.077** (.032)
AR Usage × Brand Popularity	**-.130** (.035)	**-.109** (.041)	**-.133** (.035)
AR Usage × New to Category	**.458** (.189)	**.636** (.216)	**.459** (.191)
AR Usage × New to Brand	**.420** (.186)	**.682** (.212)	**.422** (.188)
AR Usage × New to Item	**.512** (.185)	**.694** (.210)	**.519** (.186)
AR Usage × Browsers	.011 (.076)	.061 (.091)	.002 (.078)
AR Usage × Offline	-.078 (.064)	-.126 (.079)	-.084 (.064)
AR Usage × First AR Usage	-	-	-.004 (.067)
Other Variables			
Correction Term	**.366** (.069)	**.749** (.166)	**.393** (.090)
Brand / category fixed effects	Included	Included	Included
Constant	**-2.130** (.054)	**-2.120** (.055)	**-2.191** (.057)
Observations	1,515,093	1,270,774	1,515,093
Log Likelihood	-19,710	-19,076	-19,699

Notes: Robust standard errors are in parentheses; estimates that are statistically significant ($p < .05$) are in bold

3.7 Virtual vs Physical Sampling

A related inquiry is how virtual product experiences via AR (i.e., "virtual sampling") differ from sampling products physically via product testers (i.e., "physical sampling"), and whether this AR technology could be deployed in physical retail outlets to enable virtual product experiences for in-store customers. While the benefits of AR are apparent in online contexts where customers are otherwise unable to assess product fit, the impact of AR is less evident in a brick-and-mortar setting. As an extension of the research, I investigate how customers engage with AR in offline settings by conducting a follow-up field study at the retailer's store.

Compared to physical sampling, virtual sampling offers greater convenience for customers. Customers can easily select and switch between different products with the touch of a finger on the AR platform, removing the need to apply product testers. In addition, virtual sampling could also reduce barriers to physical sampling. For example, in the current research context (i.e., cosmetics industry), virtual sampling eliminates hygiene concerns of putting on intimate products (e.g., lip products) that have been used by other customers before. Additionally, virtual sampling does not require customers who are already wearing cosmetic products to remove existing products on their face.

From an operational perspective, virtual sampling is an attractive alternative to physical sampling because it confers cost and logistical advantages over physical sampling, especially when they are used in retail stores. Virtual sampling reduces costs required to provide physical product testers, which could accumulate to a substantial amount in the long run. Even though development of the AR platform requires a fixed setup cost, recurring costs to maintain the technology is negligible. Besides that, new products or collections can be easily added to the system in a timely manner. The AR platform can also accommodate a wide assortment of products because they are not constrained by physical space. As a result, retailers avoid having to make tough selection decisions on which product or brand to avail for product sampling. Furthermore, based on discussions with the focal retailer, physical samples need to be constantly monitored by retail staffs to ensure that they are placed in the designated location and are not depleted. In contrast, virtual sampling requires minimal effort to maintain, allowing retail associates to focus on other responsibilities such as customer service. Finally, as all activities on AR platforms are electronically recorded, an ancillary benefit of virtual sampling is the depth of information it supplies retailers on customers' trial behavior. Retailers would be able to ascertain the number of products sampled, order of products sampled, and duration spent on each product. Integrating these information with transaction data provides valuable insights that could be used to determine trial-to-conversion rates, forecast demand, and identify product complementarities or substitutions. Given these cost and logistical advantages, virtual sampling appears to be an attractive alternative to physical sampling.

Despite these advantages, it is unclear if virtual sampling can replace physical sampling. While virtual sampling communicates visual information about products, it is unable to convey other experiential product attributes (e.g., product texture, taste or scent). For example, while users are able to visually fit an Ikea sofa in their rooms, they are unable to assess the comfort offered from sitting on it. Similarly, users trying on make-up products virtually are unable to evaluate product texture and consistency, which may affect ease of application and the way the product feels on their skin. According to Kempf and Smith (1998), if customers do not perceive trial experiences to accurately represent actual consumption experiences, they may discount the trial experiences when they form judgements about the product. Furthermore, as consumers tend to overrate direct experiences with products (Hoch 2002; Kempf and Smith 1998), virtual sampling on AR may not be able to replace the experience of sampling products directly.

To resolve this ambiguity and examine how the option of virtual sampling changes customers' physical sampling behavior in a realistic environment, I work with the same retailer to conduct a field study. Using information on customers' in-store interactions with AR and physical product testers, I compare virtual and physical sampling along three dimensions – attraction, engagement, and exploration. Attraction refers to the power to capture shoppers' interest, engagement refers to the depth of involvement during sampling, and exploration refers to the breadth of products sampled.

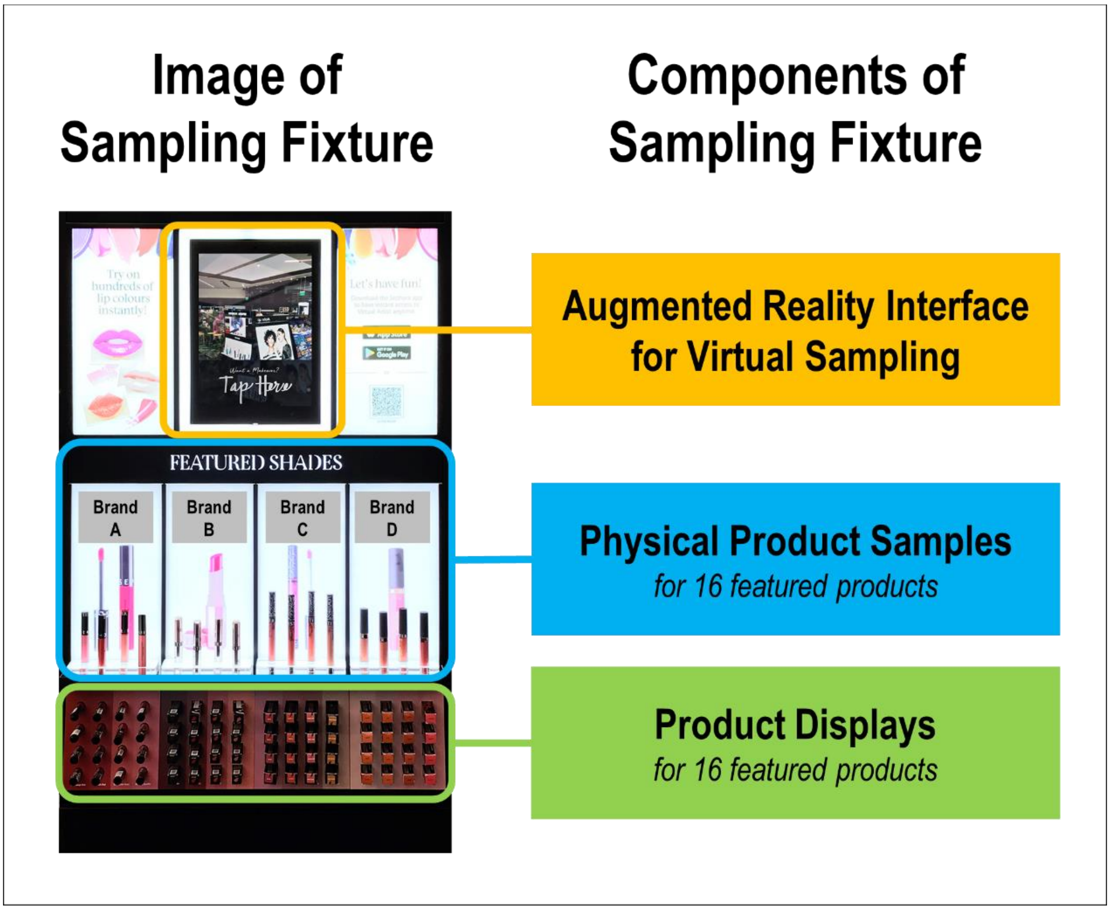
3.7.1 Field Study

The retailer introduced a sampling fixture in one of their outlets. The sampling fixture has three components – the AR interface, a physical sampling display containing physical samples of 16 featured products (i.e., 4 variants of products from 4 brands), and an in-shelf product display containing stocks for the 16 featured products. Figure 3.6 provides an image of the fixture used in the field study.

The AR interface, a touchscreen device with diagonals measuring 12.9 inches, is strategically placed at a height that allows the camera on the device to capture customers' faces. After the first touch on the screen to exit from the screensaver mode, customers would be greeted by a live view of themselves, akin to seeing a mirror reflection. At the bottom of the screen, customers can choose the product they want to virtually sample by selecting from a row of colored boxes in the shade of the

16 featured products, arranged in the same order as the physical sampling display. Similar to the mobile app, the AR technology identifies customers' facial features via the camera, and super-imposes the selected products on an image of their face in real-time. Information on the brand, product, and variant name for the selected product is provided at the bottom of the screen. Customers would also be able to discover non-featured products by swiping the screen with their fingers. In addition, they can perform directed search by filtering based on brand or shade of product.

Figure 3.6 In-store Sampling Fixture Used in Study



3.7.2 Data Description

Data for the field study is acquired from two sources:

- *Physical Interactions with Sampling Fixture:* To obtain detailed data on customers' physical interactions with the sampling fixture, the services of a company specializing in in-store tracking technology were engaged. Using video-sensing-devices mounted to the ceiling in the store, the technology captures customers' behavior when they approach the fixture (e.g., passing-by or showing interest), their physical interactions with the fixture (e.g., number, order, and duration of physical products sampled), as well as their overt characteristics (e.g., gender; if shoppers were alone or in the presence of others; if shoppers were carrying a basket) in an unobtrusive manner. This data was collected for 775 sampling sessions (including physical and/or virtual sampling) across 22 days.
- *Virtual Interaction on AR Interface*: Detailed data of shoppers' activities on the AR interface is recorded electronically. The data includes information on number and order of products sampled, and time spent on each product. Although the AR interface remained functioning throughout the field study period (as verified by the physical interaction data as well as retail associates), the virtual interaction data was not stored in the system during the last 6 days of the study. Thus, data from the first 16 days is used to analyze customers' virtual activity on the AR interface.

Shoppers' physical interactions are matched with their activities on the AR interface based on the timestamp on these two datasets, providing a holistic account of how customers engage with AR and product testers (e.g., number, variety, sequence of variants sampled). Details for the data sources is summarized in Table 3.8.

Table 3.8 Details of Data Sources

	Physical Interaction Data	**Virtual Interaction Data**
Number of Days	22	16 [a]
Information Captured	• Time spent at sampling fixture • Number, order, and duration of products sampled physically. • Indication of interest in sampling fixture and interacting with AR interface • Overt shopper characteristic (e.g., alone/with others; gender; with/without basket)	• Time spent on AR interface • Number, order, and duration of products sampled virtually.

[a.] *Virtual interaction data was not stored in the system during the last 6 days of the study, although the AR interface remained functioning throughout the study period.*

Sampling behavior are assessed using the following measures:

- *Attraction*: incidence of shoppers interacting with the AR interface and physical product samples, as well as time-to-first-interaction.
- *Engagement*: session duration and bounce rate (i.e., proportion of customers who leave after interacting with one product).
- *Exploration*: number of products sampled physically and virtually. Since non-featured products are only available on the AR interface, I analyze featured and non-featured products separately.

3.7.3 Results

A comparison between physical and virtual sampling behavior is summarized in Table 3.9. Overall, 4.69% (n=1,119) of customers who passed by showed interest in the sampling fixture. Of these, 30.74% did not interact with the fixture, 20.20% only interacted with physical samples, 40.48% only interacted with the AR interface, and 8.58% interacted with both. Among those that interacted with both, almost half (46.88%) interacted with physical samples first. Customers who interacted with the AR interface have a shorter time-to-first-interaction compared to customers who interacted with physical samples ($M_{\text{virtual}} = 8.68$, $M_{\text{physical}} = 17.27$ seconds; $p < .01$). Taken together, results suggest a stronger attraction effect of virtual sampling.

On average, customers spent 75.86 seconds ($SD = 75.05$, $Min = 1$, $Max = 471$) at the sampling fixture. Customers who interacted with the AR interface spent more time at the fixture compared to customers who interacted with physical samples ($M_{\text{virtual}} = 93.66$ vs $M_{\text{physical}} = 66.86$ seconds; $p < .01$). The bounce rate for virtual sampling (10.91%) is also lower compared to physical sampling (45.03%; $p < .01$), indicating higher engagement on the AR platform.

Comparing sampling of featured products, customers explore more products when they are sampling virtually vs physically ($M_{\text{virtual}} = 4.24$, $M_{\text{physical}} = 2.29$ out of 16 products; $p < .01$). In addition, customers who interact with the AR interface also sampled 13.24 non-featured products (i.e., products not available for physical samples; $SD = 17.02$, $Min = 0$, $Max = 135$) on average, implying that AR technology is a good platform to encourage product discovery.

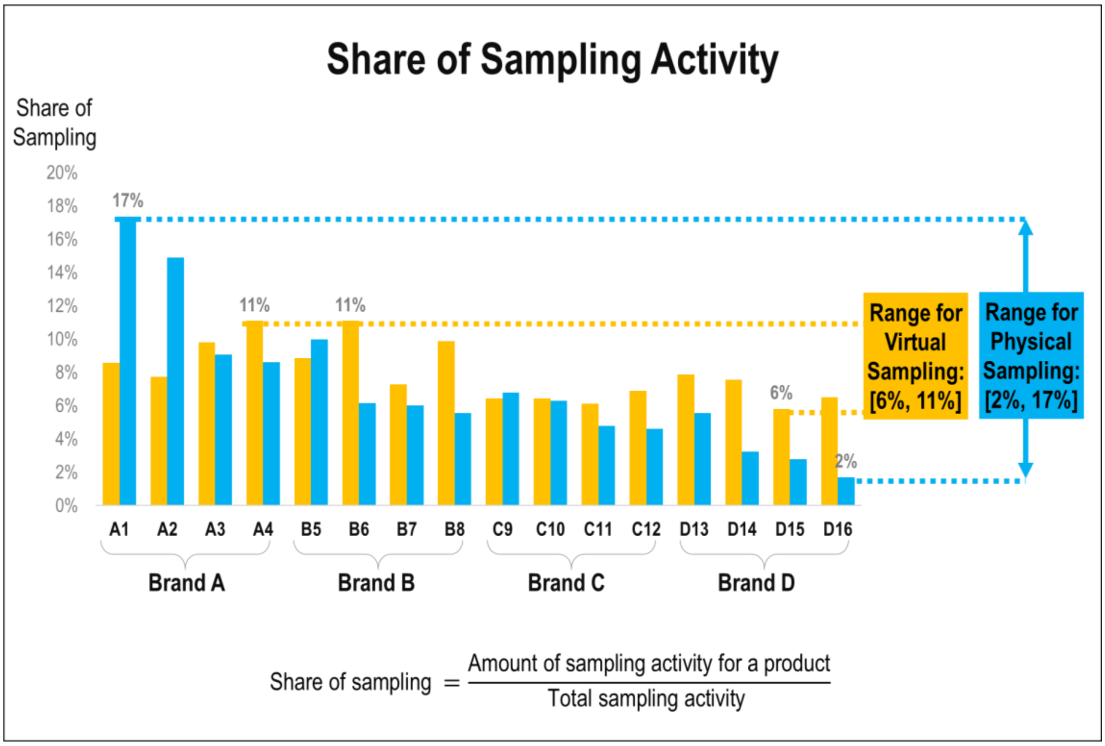
Table 3.9 Physical vs Virtual Product Sampling

	Total Sample (1)	**Sampled Physically [a] (2)**	**Sampled Virtually [a] (3)**
Attraction Effect			
% Show Interest (among those that pass by)	4.69	-	-
% Sampled Physically Only (among those that show interest)	20.20	-	-
% Sampled Virtually Only (among those that show interest)	40.48	-	-
% Sampled Physically AND Virtually (among those that show interest)	8.58	-	-
% Sampled Physically First (among those that sampled physically AND virtually)	46.88	-	-
Seconds to First Interaction [b] (among those that sampled)	6.34	17.27	8.68***
Engagement Effect (among those that sampled)			
Session Duration in seconds	75.86	66.86	93.66***
Bounce Rate [c]	23.22	45.03	10.91[e] ***
Exploration Effect (among those that sampled)			
No. of Featured Products Sampled	-	2.29	4.24 [e] ***
No. of Non-Featured Products Sampled Virtually [d]	-	-	13.24 [e]
Total No. of Products Sampled Virtually	-	-	17.49 [e]
Sample Size (shoppers who sampled)	775	322	549

** $p \leq .10$; ** $p \leq .05$; *** $p \leq .01$; Column (3) sig-tested against Column (2).*
[a] Includes those who sampled physically AND virtually
[b] For (1), first interaction with physical samples or AR interface;
for (2), first interaction with physical samples; for (3), first interaction with AR interface
[c] Bounce Rate = proportion of customers who leave after sampling one product (physically or virtually)
[d] Only featured products available for physical samples
[e] Based on available virtual interaction data (n = 394)

An examination of sampling behavior at the product level also reveal interesting differences (Figure 3.7). The share of sampling (i.e., amount of sampling activity for a product, as a proportion of total sampling activity) of physical samples range between 2% to 17% across the 16 featured products, indicating that some products are sampled more frequently than others. In addition, share of sampling for products under the same brand tend to be clustered around the same point, implying that customers' physical sampling behavior is driven by product brand. In contrast, sampling choices are fragmented on the virtual platform, with share of sampling ranging between 6% to 11%. This fragmentation pattern is even more evident for non-featured products (share of sampling less than 2.5% for all products – not shown in Figure 3.7). Thus, consistent with research in the mobile app context, AR strongly facilitates exploration of brands and products that are not featured.

Figure 3.7 Share of Sampling in Physical and Virtual Sampling Mode



I also explore how physical and virtual sampling behavior differ based on the order of sampling mode (i.e., physical sampling first or virtual sampling first). Referring to Table 3.10, results indicate that customers who virtually sampled first were less likely to physically sample more than one product (55.56%) compared to customers who physically sampled first (29.41%; $p < .05$). They also try less physical samples compared to customers who physically sampled first ($M_{\text{virtual first}} = 1.92$, $M_{\text{physical first}} = 2.62$; $p < .10$).

Table 3.10 Sampling Behavior Based on Order of Sampling Mode

	Customers who Sampled Physically AND Virtually	
	Physical First (1)	**Virtual First (2)**
Engagement Effect		
Session Duration in seconds	151.79	145.67
Physical Sampling Bounce Rate [a]	29.41	55.56**
Virtual Sampling Bounce Rate [a]	2.94	2.78
Exploration Effect		
No. of Featured Products Sampled Physically	2.62	1.92*
No. of Featured Products Sampled Virtually	6.53	6.03
No. of Non-Featured Products Sampled Virtually	14.65	19.42
Total No. of Products Sampled Virtually	21.18	25.44
Sample Size (shoppers who sampled)	45	51

** $p \leq .10$; ** $p \leq .05$; *** $p \leq .01$; Column (2) sig-tested against Column (1)*
[a] *Bounce Rate = proportion of customers who leave after sampling one product.*

Furthermore, the number of overlapping products that are both physically and virtually sampled ($M_{\text{physical first}} = 1.42$, $M_{\text{virtual first}} = 0.75$; $p < .05$), and the proportion of overlapping products out of all products physically sampled (54.40% for physical first vs 36.11% for virtual first; $p < .10$) is lower if customers virtually sample first. These results suggest that virtual sampling helps customers determine which products to sample physically by narrowing their options.

The video-sensing technology used to capture shoppers' overt characteristics identifies their social context (i.e., alone, in group, or with kids), and the gender of shoppers who are alone. As the product category is targeted towards females, there is a small sample of male shoppers (n=20), which I exclude from the analysis. Comparison of sampling behavior between female shoppers who are alone versus shoppers who are in groups or with kids are presented in Table 3.11.

Referring to column (1) to (3) in Table 3.11, shoppers in the presence of others are more likely to show interest in the sampling fixture. Compared to individual shoppers (2.72%), shoppers in groups (10.84%; $p < .01$) or with kids (9.50%; $p < .01$) are more likely to pause in front of the sampling fixture. Among those that do show interest, individual shoppers prefer to sample products physically (34.58%) instead of virtually (19.63%). Individual shoppers were also significantly less likely to use both sampling modes (4.00%) compared to shoppers in groups (12.75%; $p < .01$). In contrast, shoppers in groups (53.73%) or with kids (60.44%) are strongly inclined to interact with the AR interface compared to physical samples (12.02% and 12.09% respectively). Shoppers in groups are also more hesitant to sample products physically, as indicated by their longer time-to-first-interaction compared to individual shoppers ($M_{\text{individual}} = 10.05$, $M_{\text{group}} = 24.37$ seconds; $p < .01$).

In terms of engagement, individual shoppers spend less time interacting with the sampling fixture compared to shoppers who are in groups or with kids ($M_{\text{individual}} = 52.56$, $M_{\text{group}} = 90.89$, $M_{\text{kids}} = 79.19$ seconds; $p < .01$). However, individual shoppers who interacted with the AR interface spent twice as much time as those who sampled products physically ($M_{\text{virtual}} = 85.59$, $M_{\text{physical}} = 40.82$ seconds; $p < .01$).

Table 3.11. Effects of Social Context

	Social Context		
	Individual Shoppers (1)	**Shoppers In Groups (2)**	**Shoppers With Kids (3)**
Attraction Effect			
% Show Interest (among those that pass by)	2.72	10.84***	9.50***
% Sampled Physically Only (among those that show interest)	34.58	12.02***	12.09***
% Sampled Virtually Only (among those that show interest)	19.63	53.73***	60.44***
% Sampled Physically AND Virtually (among those that show interest)	4.00	12.75***	9.89**
% Sampled Physically First (among those that sampled physically AND virtually)	47.06	45.71	55.56
Seconds to First Physical Interaction (among those that sampled physically)	10.05	24.37***	29.25
Seconds to First Virtual Interaction (among those that sampled virtually)	8.64	8.86	8.88
Engagement Effect (among those that sampled)			
Session Duration in seconds	52.56	90.89***	79.19***
Physical Sampling Bounce Rate [b]	43.03	44.85	60.00
Virtual Sampling Bounce Rate [a, b]	17.57	5.88***	14.89
Exploration Effect (among those that sampled)			
No. of Featured Products Sampled Physically	2.25	2.42	1.80
No. of Featured Products Sampled Virtually [a]	3.91	4.72	3.09
No. of Non-Featured Products Sampled Virtually [a]	12.36	14.46	12.40
Total No. of Products Sampled Virtually [a]	16.27	19.18	15.49
Sample Size (shoppers who sampled)	249	431	75

** $p \leq .10$; ** $p \leq .05$; *** $p \leq .01$; Column (2) and (3) sig-tested against Column (1)*
[a] Based on available virtual interaction data (n = 394); [b] Bounce Rate = proportion of customers who leave after sampling one product

3.7.4 Summary of Findings

To summarize findings from the in-store field study, virtual sampling is superior to physical sampling in terms of attracting and engaging customers. By reducing friction in the product sampling process, virtual sampling also encourages greater product exploration, benefiting less-popular products that normally have low sampling rates. These results are consistent with the mobile app study, providing further validity to our findings.

The results also suggest that when both product testers and AR are available, customers use virtual sampling complements physical sampling in the decision-making process by helping customers narrow their choices prior to using product testers. In addition, AR has strong appeal among customers who are in the presence of others (i.e., in groups or with kids), indicating that the technology is experienced as a social activity and provides additional entertainment value. Nevertheless, individual female shoppers still prefer to use physical samples, suggesting that virtual sampling is not able to substitute physical sampling.

3.8 Conclusion

Taken together, I find that customers display higher levels of involvement when they use AR, highlighting the technology's potential to improve customer engagement. By enabling customers to assess product fit through virtual product experiences, AR encourages customers to explore more brands and products that they have never purchased before. Virtual product experience also reduces product-related uncertainty and increases customers' confidence in online purchases. Consequently, the use of AR diminishes the importance of extrinsic product quality cues and improves preferences for cheaper products and less-popular brands.

Even though AR is rapidly gaining prominence, there is still a lack of clarity surrounding its application in marketing contexts. The present research represents an initial step to understand how AR can be applied in marketing contexts to engage customers and influence purchase. To the best of my knowledge, this is the first study to examine AR using data from actual customers' interactions in field settings, adding to research on this emerging technology.

3.8.1 Managerial Implications

Findings from these studies offers some key insights for online and offline retailers. Firstly, retailers can use AR to improve customer engagement. According to eMarketer (2018b), customers spend just 3.3 minutes per week on a retail app on average. This mobile app study suggest that online retailers can use AR to increase engagement, especially among browsers or customers who have never purchased online before. Similarly, offline retailers can use AR to engage customers and appeal to the hedonistic aspect of shopping experience (Babin, Darden, and Griffin 1994). These positive shopping experiences could directly increase purchase probabilities, or may indirectly influence sales by generating word of mouth.

Secondly, given that virtual product experiences increase product discovery and exploratory purchases, retailers can use AR as a cross-selling opportunity to increase customers' consideration for categories or brands they have never purchased before.

Thirdly, by reducing friction in the sampling process, AR increases consideration and trial for products that are less popular. Thus, retailers carrying wide assortments of brands can use AR as a democratizer to level the playing field for less-popular brands. Furthermore, less established brands could consider investing in AR-enabled ads on Facebook when the feature becomes available.

3.8.2 Limitations & Future Research Opportunities

I acknowledge some limitations in the studies, which present worthwhile opportunities for further research. The mobile app study uses data from a single online retailer, and I do not observe customers' purchases from other retailers. Thus, my classification of customers based on their prior product experience (e.g., new to category or brand) is based only on their previous purchases with the focal retailer. Nevertheless, since the retailer is the dominant player in the region where the data is collected, I believe that this issue has minimal influence on the validity of my findings. Future research could extend the study across different retailers or industries to assess the generalizability of the findings.

The mobile app study also focuses on the immediate impact of AR usage on engagement and purchase; the field would benefit from further investigation into the longer-term effects of the technology, such as its influence on frequency of app visits and customer value over a period of time. Due to hygiene reasons, the retailer in this study only accepts product returns for defective products, but it is also worth investigating if the ability to experience products virtually lowers product returns due to poor product fit (e.g., Bell et al. 2018, Gallino and Moreno 2018). Additionally, the spill-over effects of virtual product experience on subsequent in-store visits and purchases would also be of interest to omnichannel retailers.

In the field study, there could be some element of self-selection as customers were not randomly assigned to use physical and virtual sampling. Nevertheless, this limitation does not take away from the key contribution of the study, which are the insights on how shoppers interact with physical and virtual sampling in actual field settings. Furthermore, due to the constrain arising from the store layout, I am not able to directly link sampling behavior with purchase conversion at the customer-level to quantify the conversion effects. Future research could compare the effects of in-store physical and virtual sampling behavior on purchase probabilities and product preferences.

Notwithstanding these limitations, I believe the valuable and managerially relevant insights from these studies would help retailers determine if they should incorporate AR technology in their mobile apps or in stores.

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