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Augmented reality in retail and its impact on sales

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Augmented Reality in Retail and its Impact on Sales

Abstract

The rise of Augmented Reality (AR) technology presents marketers with promising opportunities to engage customers and transform their brand experience. While firms are keen to invest in AR, research documenting its tangible impact in real-world contexts is sparse. In this article, the authors outline four broad uses of the technology in retail settings. Next, they focus specifically on the use of AR to facilitate product evaluation prior to purchase, and empirically investigate its impact on sales in online retail. Using data obtained from an international cosmetics retailer, they find that AR usage on the retailer's mobile app is associated with higher sales for brands that are less popular, products with narrower appeal, and products that are more expensive. In addition, the effect of AR is stronger for customers who are new to the online channel or product category, suggesting that the sales increase is coming from online channel adoption and category expansion. These findings provide converging evidence that AR is most effective when product-related uncertainty is high, demonstrating the technology's potential to increase sales by reducing uncertainty and instilling purchase confidence. To encourage more impactful research in this area, the authors conclude with a research agenda for AR in marketing.

Keywords: Augmented Reality, online retail, mobile app, virtual product experience, product uncertainty

"At some point, we're going to look back and think, how did we not have a digital layer on the physical world?"

– Greg Jones, Director of VR and AR at Google

Augmented Reality (AR) is a technology that superimposes virtual objects onto a live view of physical environments, helping users visualize how these objects fit into their physical world. Even though AR is in its early stages of growth, leaders in the field, including Apple CEO, Tim Cook, and Google's Director of Virtual Reality (VR) and AR, Greg Jones (Forbes 2017; Independent 2017), have lauded its potential to transform the retail experience. With the launch of AR toolkits by technology giants Apple and Google, it is now easier for companies to develop their own AR-enabled mobile apps. Jumping on the bandwagon, Facebook recently introduced AR-enabled display advertisements for their News Feed (Business Insider 2019), making the technology even more accessible to companies.

From a retail perspective, a promising application of AR is to facilitate product evaluation by letting customers experience products virtually prior to purchase. While research has emphasized the importance of direct product experiences to help customers learn about product benefits and assess product fit (e.g., Bell, Gallino, and Moreno 2018; Chandukala, Dotson, and Liu 2017), offering direct product experiences can be a logistical challenge, especially in online retail. The introduction of AR opens the possibility for shoppers to experience products virtually in the absence of physical products, managing their expectations and instilling purchase confidence (Porter and Heppelmann 2017). For example, Amazon and Ikea are using this technology to help customers determine if online products or furniture pieces are compatible with their existing room décor; Tiffany & Co. have used AR to help shoppers visualize how engagement rings will look on their hands; and L'Oréal and Sephora are using AR to offer customers realistic previews of their appearances with different cosmetic products. Some of these applications are illustrated in Web Appendix A.

Despite the keen interest in AR, there has been limited research demonstrating its tangible impact in real-world contexts. Understanding the potential for AR to increase revenues is important in order to justify investments in this new technology. However, the impact of AR on actual product sales is still ambiguous. By helping customers visualize products in their consumption contexts, AR could reduce product fit uncertainty, resulting in more sales. Conversely, AR may also discourage purchases if it leads to perceptions that the products may not fit well. As the technology is unable to convey experiential product attributes that could be important in purchase decisions (e.g., product texture or scent), the impact of AR on sales could also be insignificant. This uncertainty surrounding the impact of AR has been cited as one of the main reasons why companies are still hesitant to embrace the technology, even though most recognize the exciting opportunities it offers (BCG 2018). Echoing this lack of clarity, a recent article regarding applications of AR in the cosmetics industry expressed that “Virtual lipsticks and smokey eye shadows are popular in apps, but are they translating into more makeup sales? Hard data isn't easy to come by” (CNN 2019).

Furthermore, whether and how the impact of AR varies across different products or customer segments is also unclear. Having a more nuanced understanding of how AR affects sales would help marketing managers determine when it would be most appropriate to deploy the technology. Conceivably, if AR increases sales by reducing uncertainty, its impact may depend on product and customer characteristics that influence uncertainty in purchase decisions, such as brand popularity, product appeal, and customers’ familiarity with the retail channel or category. Accordingly, the present research adopts the retailers’ perspective to examine the following questions:

1) How does the use of AR to facilitate product evaluation impact product sales?
2) How does the sales impact of AR usage differ across product characteristics, such as brand popularity, product appeal, rating, and price?

3) How do customers' prior experiences with the online channel and product category influence the sales impact of AR usage?

Given that AR is predominantly available on mobile apps (eMarketer 2020), we focus on the mobile app platform for our analyses. We obtained data from an international cosmetics retailer who incorporated AR into their mobile app to help customers realistically visualize how they look with different cosmetic products (e.g., eyeshadows, lipsticks). The data contain sales records for 2,300 products, as well as browsing and purchase histories for 160,400 customers, allowing us to investigate how the sales impact of AR varies by product and customer characteristics. In addition, introduction of the AR feature for two product categories during the observation period provided us with a quasi-experimental setting to examine the impact of AR introduction on category sales.

Findings from our research provide preliminary evidence that AR usage has a positive impact on product sales. The overall impact appears to be small, but certain products are more likely to benefit from the technology than others. In particular, the impact of AR is stronger for brands that are less popular and products with narrower appeal, suggesting that AR could level the playing field for niche brands or products at the long tail of the sales distribution. The increase in sales is also greater for products that are more expensive, indicating that AR could increase overall revenues for retailers. Additionally, customers who are new to the online channel or product category are more likely to purchase after using AR, suggesting that AR has the potential to promote online channel adoption and category expansion. These findings provide converging evidence that AR is most effective when product-related uncertainty is high, implying that uncertainty reduction could be a possible mechanism for AR to improve sales.

The present research is one of the first to empirically demonstrate the impact of AR on sales and how it varies across product and customer characteristics using real-world data.

In doing so, it extends prior studies on AR in the marketing field, and represents an initial step to understand what AR means for marketers and retailers. Beyond influencing sales, AR could transform the way brands reach out to, and connect with customers at different stages of the customer journey. In the following section, we provide an overview of AR, and elaborate on four ways the technology can be incorporated into brands' marketing strategies to reshape the customer retail experience. Next, we focus specifically on how the use of AR to facilitate product evaluation prior to purchase impacts sales in online retail. To encourage marketing academics to further engage in impactful and managerially-relevant research in this area, we conclude with a research agenda that is developed based on surveys with marketing practitioners.

Augmented Reality

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 virtual 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 also responsive to movements or gestures, creating an interactive experience for users.

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 virtual elements to it, VR immerses users in a completely digital environment - users are virtually transported to an artificial, simulated world, and are entirely shut out of their surroundings. Due to the disorienting experience of being entirely isolated from the real world and the expensive headsets required (Ericsson 2017), the appeal of VR has largely been limited to industries with products high in simulated content, such as gaming and entertainment (Forbes 2018). In contrast, AR 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 handheld devices that users already own (e.g., tablets or smartphones). Thus, AR is rapidly gaining prominence and by 2022, close to 100 million US consumers are expected to use the technology regularly (eMarketer 2020).

Augmented Reality in Retail

The unique capabilities of AR present marketers with new opportunities to engage customers and transform the brand experience. Based on an extensive review of current applications of AR, we identified four broad uses of the technology in retail settings – to *entertain* and *educate* customers, help them *evaluate* product fit, and *enhance* the post-purchase consumption experience. These uses loosely correspond to customers' journey from awareness to interest, consideration, purchase, and consumption, and may not be mutually exclusive. We elaborate on the four uses below, and provide a summary with relevant examples in Table 1[1].

-----Insert Table 1 here-----

Entertain. 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 and entertain customers. Besides generating hype and interest, marketers have also used AR-

[1] URL links to these examples are provided in Web Appendix B.

enabled experiences to drive traffic to their physical locations. For example, Walmart collaborated with media companies such as DC Comics and Marvel to bring exclusive superhero-themed AR experiences to their stores by placing special thematic displays around selected outlets. In addition to creating novel and engaging experiences for customers, it also encouraged them to explore different areas within the stores.

Educate. Due to its interactive and immersive format, AR is also an effective medium to deliver content and information to customers. For instance, to help customers better appreciate their new car models, Toyota and Hyundai have utilized AR to demonstrate key features and innovative technologies in a vivid and visually appealing manner. AR can also be used to help customers navigate in retail stores, or highlight relevant product information to influence in-store purchase decisions. Retailers such as Walgreen and Lowe's have developed in-store navigation apps that overlay directional signals onto a live view of the path in front of users to guide them to product locations, and notify them if there are special promotions along the way.

Evaluate. By retaining the physical environment as a backdrop to virtual elements, AR also helps users visualize how products would appear in their actual consumption contexts, allowing them to more accurately assess product fit prior to purchase. For example, Ikea's Place app uses AR to give customers a preview of different furniture pieces in their homes by overlaying true-to-scale, 3-dimensional models of products onto a live view of the room. Customers can easily determine if the products fit in a given space without the hassle of taking any measurements. Fashion retailers Uniqlo and Topshop have also deployed the same technology in their physical stores, offering customers greater convenience by reducing the need to change in and out of different outfits. An added advantage of AR is its ability to accommodate a wide assortment of products. By replacing tangible product displays with lifelike virtual previews of products, retailers can overcome the constraints of physical space while still offering customers the opportunity to explore different product options. This capability is particularly useful for made-to-order or bulky products. Car manufacturers BMW and Audi have used AR to provide customers with true-to-scale, 3-dimensional visual representations of car models based on customized features such as paint color, wheel design, and interior aesthetics. These cases exemplify AR's huge potential to increase customers' confidence in their purchase decisions for a variety of products.

Enhance. Lastly, AR can be used to enhance and redefine the way products are experienced or consumed *after* they have been purchased. For example, Lego recently launched several brick sets that are specially designed to combine physical and virtual gameplay. Through the companion AR app, animated Lego characters spring to life and interact with the physical Lego sets, creating a whole new playing experience. In a bid to address skepticism about the quality of its food ingredients, McDonald's has also used AR to let customers discover the origins of ingredients in the food they purchased via story-telling and 3-dimensional animations.

The present research focuses on the use of AR to help customers evaluate products prior to purchase. Specifically, we explore the possibility of leveraging AR to reduce product-related uncertainty in online purchase decisions. To extend prior research on AR in retail (summarized in Table 2), we use real-world data to examine how customers' use of AR to try products (for brevity, we refer to this as "AR usage" for the rest of the paper) affect product and brand sales. In the following section, we present our conceptual framework and develop hypotheses for the impact of AR usage on sales.

-----Insert Table 2 here-----

Conceptual Framework

Product Uncertainty in Online Retail

As consequences of purchase decisions cannot be perfectly predicted by customers, uncertainty is inherent in market exchanges (Bauer 1960). However, it is especially pronounced in online environments due to the spatial separation between buyers and sellers, and temporal separation between payment and product fulfillment (Burke 2002; Pavlou, Liang, and Xue 2007). Unlike traditional retail, customers are unable to physically inspect or evaluate products before making a purchase, resulting in greater uncertainty that the products would be able to deliver the expected level of performance or benefits (Bell, Gallino, and Moreno 2018; Dimoka, Hong, and Pavlou 2012; Kim and Krishnan 2015).

Researchers have broadly distinguished between two types of product uncertainty in online markets. Product performance uncertainty occurs when customers are unable to evaluate or predict product performance due to imperfect knowledge (Dimoka, Hong, and Pavlou 2012). In contrast, product fit uncertainty occurs when customers are unable to determine if the product matches their needs (Bell, Gallino, and Moreno 2018; Hong and Pavlou 2014). The latter form of uncertainty is typically higher for products with experience attributes (i.e., attributes that can only be evaluated after the product has been experienced, Hong and Pavlou 2014), such as apparel or beauty products.

Several mechanisms to reduce product performance uncertainty in online retail have been suggested. For example, retailers could lower information asymmetry by providing diagnostic product descriptions, or include credibility signals such as third-party product assurances, warranties, or customer reviews (Dimoka, Hong, and Pavlou 2012; Weathers, Sharma, and Wood 2007). On the contrary, product fit uncertainty typically requires direct product experience to resolve, as it is idiosyncratic in nature and varies from individual to individual. While some retailers have adopted try-before-you-buy programs (e.g., Warby Parker's home try-on program, Bell, Gallino, and Moreno 2018) or lenient product return policies (Gu and Tayi 2015; Wood 2001) to provide opportunities for direct product experiences, these measures are notoriously costly for retailers due to the additional shipping and handling costs, and risks of product damage (Financial Times 2019). Furthermore, direct product experiences may not be viable or appropriate in certain cases, for example, if the product is customized (e.g., engagement rings), related to personal care (e.g., cosmetic products), or requires assembly (e.g., furniture).

Augmented Reality and Product Uncertainty

The introduction of AR opens the possibility of substituting direct product experiences with virtual product experiences to facilitate product evaluation and reduce product fit uncertainty. Using a situated cognition perspective, Hilken et al. (2017) proposed that the value of AR lies in its ability to help customers visually integrate virtual products into the real-world environment (i.e., "environmental embedding"), and use bodily movements and physical actions to control how products are presented (i.e., "simulated physical control"). The unique combination of these two properties induces perceptions that the virtual products are physically present in the real world, creating realistic product experiences. Consequently, customers are able to evaluate products as if they are interacting with the actual products, reducing product fit uncertainty as a result. In line with this, prior research has found that vivid images and greater control over the presentation of information are effective ways to alleviate uncertainty in online environments (Weathers, Sharma, and Wood 2007). By helping customers visualize products in their consumption contexts and reducing product fit uncertainty, AR-enabled product experiences increase the level of ease customers feel in the decision-making process, translating to positive behavioral intentions (Heller et al. 2019a; Hilken et al. 2017).

However, while AR communicates visual information about products, it is unable to convey other experiential product attributes (e.g., product texture or scent). For example, although customers may use AR to visualize an Ikea sofa in their rooms, they are unable to assess how comfortable it is. Similarly, users trying on cosmetic products via AR are unable to evaluate product texture and consistency, attributes which may affect ease of application and the way the product feels on the skin. According to Kempf and Smith (1998), if customers do not perceive trial experiences to accurately represent actual consumption experiences, they may discount those trial experiences when they form judgements about the product. Hence, the extent to which virtual product experiences on AR could influence online purchases is unclear. Nevertheless, as prior research has demonstrated the positive effects of providing fit information in online retail (e.g., Gallino and Moreno 2018; Kim and Forsythe 2008), we expect AR usage to have a positive impact on product sales because the technology could similarly convey visual information which may reduce product fit uncertainty in online purchase decisions. Hence, we predict that

H1: AR usage has a positive impact on sales.

Building on the proposition that AR usage increases sales by reducing product fit uncertainty, we further hypothesize that AR would have a stronger impact when customers experience higher levels of uncertainty. In particular, the level of uncertainty experienced in a purchase decision could depend on product characteristics such as brand popularity, product appeal, and ratings. The level of uncertainty may also influence the price that customers are willing to pay for the product. Thus, the relationship between AR usage and sales may differ across these product characteristics. Additionally, customers also vary in their need to reduce product fit uncertainty before making a purchase (Bell, Gallino, and Moreno 2018). This need to reduce uncertainty could depend on customers' familiarity with the online channel and product category. As a result, the impact of AR may also vary across these customer characteristics. Accordingly, we develop hypotheses for the moderating effects of product and customer characteristics in the following sections. Our conceptual framework is presented in Figure 1.

-----Insert Figure 1 here-----

Moderating Effects of Product Characteristics

Brand popularity. Prior research has shown that consumers are more cautious when they purchase from brands that are less well-known, as they anticipate feeling more regret if the product turns out to be inferior (Simonson 1992). Consistent with this, Erdem, Swait, and Valenzuela (2006) found that cultures that are high on uncertainty-avoidance place greater emphasis on brand credibility. In online environments, brand signals are even more important because consumers are not able to inspect products before purchasing (Danaher, Wilson, and Davis 2003). However, Hollenbeck (2018) demonstrated that when additional information is available to facilitate decision-making, consumers rely less on brand signals. As a result, less-established brands benefit more from the increased availability of information. In the same vein, by communicating visual information to help customers assess product fit, AR may reduce uncertainty in online purchase decisions. Consequently, AR may decrease customers' reliance on brand signals and inadvertently increase preference for brands that are less popular. We use the term "popular" in a general sense to refer to brands that are more widely adopted. Hence, we hypothesize that

H2a: The impact of AR usage on sales will be stronger for brands that are less popular

Product appeal. Within the same category or brand, products may also have different levels of appeal due to the alignment between their inherent characteristics and general consumer preferences. For example, a red lipstick is more mainstream and has broader appeal compared to a blue lipstick. We draw a distinction between brand popularity and product appeal – the latter depends on intrinsic properties of the product and could be independent of the brand. Thus, a red lipstick from an unknown brand could have broad appeal but low brand popularity, while a blue lipstick from a well-known brand could have limited appeal despite having high brand popularity. As products with broad appeal cater to the masses, they are more likely to match the needs of the general consumer. Conversely, since products with narrower appeal (sometimes referred to as products at the "long tail" of the product sales distribution, e.g., Brynjolfsson, Hu, and Simester 2011) serve a niche segment, there is a higher probability that they will not match the preferences of the general consumer and thus, carry greater product fit uncertainty. Nevertheless, Brynjolfsson, Hu, and Simester (2011) demonstrated that in online contexts, search and discovery features, such as search tools or recommendation engines, can shift consumers' preferences to niche products by lowering the cost of acquiring product information. Consistent with this, Tucker and Zhang (2011) found that products with narrower appeal benefit more from greater information availability. By visually conveying product information to help customers assess product fit in an effortless and risk-free environment, AR could similarly have a stronger impact for products with narrower appeal due to the higher product fit uncertainty associated with these products. Therefore, we hypothesize that

H2b: The impact of AR usage on sales will be stronger for products with narrower appeal

Ratings. Customers often turn to online ratings or reviews as a source of information to resolve uncertainty about product quality and fit (Chen and Xie 2008). In line with this, Kübler et al. (2018) found that consumers from countries that are high on uncertainty avoidance are more sensitive to both the valence and volume of product ratings. However, as consumers tend to overrate direct experiences with products (Hoch 2002), the ability to evaluate products and resolve uncertainty via first-hand experiences on AR may reduce customers' reliance on online ratings. Thus, by enabling customers to learn about product benefits and assess product fit through their own virtual experiences, AR could diminish the role of online ratings in purchase decisions. As a result, when customers are able to try products on AR, they may be more amenable to purchase these products despite their lower ratings. Hence, we predict that

H2c: The impact of AR usage on sales will be stronger for products with lower ratings

Price. When customers experience product uncertainty, they are not able to accurately assess the benefits offered by products. As a result, customers are more likely to undervalue products, and would be less willing to pay a premium (Dimoka, Hong, and Pavlou 2012). Consistent with this, Kim and Krishnan (2015) found that when there is a high degree of product uncertainty, customers who are familiar with online shopping are still hesitant to purchase expensive products through the internet because they could suffer greater financial losses if these products do not fit them well. By facilitating product evaluation prior to purchase, AR helps customers ascertain if products match their needs and preferences. Consequently, customers may experience less uncertainty and feel more comfortable purchasing products that are more expensive. In line with this, Heller et al. (2019b) found that AR usage improves decision comfort, leading to higher willingness to pay. Hence, we predict that

H2d: The impact of AR usage on sales will be stronger for more expensive products

Moderating Effects of Customer Characteristics

Channel experience. According to Kim and Krishnan (2015), customers who are familiar with online shopping are more inclined to purchase products with a higher degree of uncertainty because their cumulative online shopping experiences help them develop the ability to assess products when limited information is available. Thus, customers who have purchased from a retailer’s online channel in the past may feel more comfortable making subsequent online purchases despite experiencing product uncertainty, and may be less dependent on AR to make their purchase decisions. In contrast, customers who are new to the retailer's online channel (but have made prior purchases at the retailer's offline channel) are not accustomed to making purchases in the absence of actual products. As a result, they may experience greater product fit uncertainty, and may be deterred from purchasing online due to the inability to assess product fit. Since AR simulates the in-store experience of trying products, it may help to reduce product fit uncertainty for customers who are new to the online channel. These customers may derive greater value from the ability to evaluate products virtually, and could be more likely to purchase online after using AR. Hence, we predict that

H3a: The impact of AR usage on sales will be stronger for customers who are new to the retailer's online channel.

Category experience. Besides channel experience, customers' familiarity with the product category also affects their level of product fit uncertainty (Hong and Pavlou 2014). Customers who are familiar with a product category can draw on their prior experiences as an information source to form judgements about products (Smith and Swinyard 1982). As a result, they may rely less on AR in their purchase decisions. Conversely, customers who are unfamiliar with a product category lack the necessary category knowledge to evaluate product attributes and at the same time, may not be aware of their own preferences (Hong and Pavlou 2014). Consequently, they will have more difficulty assessing if a product's attributes match their preferences, resulting in greater product fit uncertainty. By helping customers visualize how products would appear in their actual consumption contexts, AR could reduce product fit uncertainty and increase purchase confidence for customers who are new to the product category. As a result, AR usage may have a stronger impact on the purchase decisions for these customers. Therefore, we predict that

H3b: The impact of AR usage on sales will be stronger for customers who are new to the product category.

To summarize, we propose that AR usage will positively impact sales by reducing product uncertainty. Following this line of reasoning, we developed several predictions about which products are more likely to benefit from AR, and which customers are more likely to respond to AR.

Empirical Analysis

Empirical Context

As AR is predominantly available on mobile apps (eMarketer 2020), we focus our analyses on the mobile app platform. To test our hypotheses, we obtained data from an international cosmetics retailer with 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., eyeshadows, lipsticks). The AR technology detects customers' facial features via their smartphone cameras and super-imposes the shade of chosen products onto a live view of their face in real-time, giving them a realistic visual representation of their appearances when they use the products. The brand, product name, and price are displayed at the top of the screen. Figure A3 in Web Appendix A provides a visual example of a customer trying on a lipstick using the AR feature. For comparison, the corresponding product detail page view (i.e., the conventional way of conveying product-related information on mobile retail apps) is also provided. Prior to the start of our observation period in December 2017, the AR feature was only available for lip categories (i.e., lipstick and lip gloss), and was subsequently introduced for eye categories (i.e., eyeshadow and eyeliner) in March 2018. Figure A4 in Web Appendix A provides a visual overview of AR availability for the different categories.

We obtained two separate datasets from the retailer for one of its key markets in Asia Pacific. The first dataset contains information about browsing activities on the mobile app, including specific products that customers tried using the AR feature. This dataset covers a 19-month period from December 2017 to June 2019. The second dataset contains transaction records from June 2017 to June 2019 for all retail channels, including mobile app, website, and offline stores. These two datasets are merged using customers' loyalty card number, allowing us to match AR usage and product purchases at a disaggregate level.

During the 19-month period, a total of 160,407 shoppers browsed products from the lip and eye categories across 806,029 sessions, 20.8% of which involved AR usage. Customers who used AR during the session spent 20.7% more time browsing ($M_{\text{With AR}}$ = 16.6 minutes, $M_{\text{Without AR}}$ = 13.8 minutes, $p < .01$), and browsed 1.28 times more products ($M_{\text{With AR}}$ = 53.9, $M_{\text{Without AR}}$ = 42.2, $p < .01$). The purchase rate for sessions with AR usage was 19.8% higher than sessions without AR usage (3.15% with AR vs. 2.63% without AR, $p < .01$), providing preliminary indication of the positive impact of AR on sales.

We divide our analyses into three sections. In the first section, we perform the analysis at the product-level to examine the moderating effects of brand popularity, product appeal, rating, and price. To minimize selection bias arising from availability of the AR feature, we focus on lipsticks and lip glosses, as the feature was available for more than 96% of products in each of these categories. In the second section, we take advantage of the introduction of AR for two eye categories (i.e., eyeshadow and eyeliner) to examine the effect of AR introduction on category sales using a quasi-experimental differences-in-differences-in-differences (DDD) approach. Finally, we investigate how the impact of AR varies at the customer-level. As all customers were not aware that the AR feature would be introduced for the two eye categories beforehand, the event provided us with a clean setting to examine how customers' channel and category experience (prior to the introduction) moderate the impact of AR usage on purchase probability.

Product-level Analysis

As product color is an important factor in cosmetic purchases, we consider each shade/color of retail merchandise as a unique product. In total, we have 2,334 products in the lipstick and lip gloss categories (1,984 products across 41 brands for lipstick; 350 products across 28 brands for lip gloss). Our empirical strategy is to relate the number of customers trying each product on AR during a particular time period with sales volume for the same time period. We estimated the model at the monthly-product level, giving us a total of 44,346 observations (2,334 products × 19 months from Dec 2017 to June 2019). As one of our objectives is to examine the moderating effect of product ratings, we included products with a rating in the main analysis, and replicated the analysis for all products as a robustness check. Our final sample for the main analysis consists of 29,345 observations.

Model specification. For each product i, we model how the volume of AR usage in month t, AR Usage_{it}, influences the number of products sold in month t, Product Sales_{it}. As Product Sales_{it} is a count variable with significant over-dispersion (M = 0.46, SD = 1.73), and over 80% of observations are "0", we use a zero-inflated negative binomial model for the estimation. The vector of covariates in the regression is given by the following equation:

$$
\begin{aligned}
(1)\quad \mathbf{X_{it}\beta} = {} & \beta_0 + \beta_1\text{AR Usage}_{it} + \beta_2\text{Brand Popularity}_{it} + \beta_3\text{Appeal}_{it} + \beta_4\text{Rating}_{it} + \beta_5\text{Price}_{it} \\
& + \beta_6\text{AR Usage}_{it} \times \text{Brand Popularity}_{it} + \beta_7\text{AR Usage}_{it} \times \text{Appeal}_{it} \\
& + \beta_8\text{AR Usage}_{it} \times \text{Rating}_{it} + \beta_9\text{AR Usage}_{it} \times \text{Price}_{it} \\
& + \beta_{10}\text{Category}_i + \sum_{m=1}^{T-1} \delta_m\text{Month}_t + \varepsilon_{it}
\end{aligned}
$$

In Equation (1), AR Usage_{it} is measured as the number of customers using AR to try product i during month t. As brands that are more widely adopted should have higher sales, and since the web and app channels are both online in nature and carry identical products, we use total brand sales (within the category) from the web channel during the same period as a proxy for brand popularity, Brand Popularity$_{it}$. Following prior research using product sales as an indicator of mass or niche appeal (e.g., Brynjolfsson, Hu, and Simester 2011), we use total product sales from the web channel during the same period to reflect product i's breadth of appeal, Appeal$_{it}$. Rating$_{it}$ and Price$_{it}$ are the rating and price of product i at time t, respectively. To examine how the impact of AR is influenced by brand popularity, product appeal, rating, and price, we included the corresponding interactions in the model. Additionally, we included Category$_i$ (1 = lipstick, 0 = lip gloss) and a series of dummy variables, Month$_t$, (for t = 1,…,T months) to control for category and month effects. Table 3 provides a summary of how the variables are operationalized and their descriptive statistics, while their correlations are provided in Web Appendix C. All the correlations are low and the variance inflation factors (VIF) are below 1.62, indicating that multi-collinearity is not an issue. To prevent overestimation of effects due to the panel structure of the data, standard errors are clustered at the product level (e.g., Tucker 2014).

-------Insert Table 3 here-------

Identification strategy. Our objective is to understand how the volume of AR usage for product i during month t, AR Usage$_{it}$, influences product sales, Product Sales$_{it}$. However, AR Usage$_{it}$ could be endogeneous, as customers may be more inclined to use AR to try products that they are interested in purchasing. To account for this endogeneity, we use the two-stage residual inclusion method (Terza, Basu, and Rathouz 2008), which has been used in recent research when both the endogenous and dependent variables are non-linear (e.g., Arora, ter Hofstede, and Mahajan 2017; Danaher et al. 2020).

Following the two-stage residual inclusion method, we first regress the endogeneous variable, AR Usage$_{it}$, on all other covariates in Equation (1). Residuals from this first stage are then included to estimate Product $Sales_{it}$. Similar to the control function approach (Petrin and Train 2010), the included residuals control for the portion of the endogeneous variable that would otherwise correlate with the error term in Equation (1). According to Terza, Basu, and Rathouz (2008), we need to include instruments in the first stage estimation to resolve the identification problem in Equation (1). These instruments should (i) be strongly related to the endogenous variable, and (ii) not be correlated with the error term in Equation (1). In other words, the instruments should only have an indirect relationship with the outcome variable, Product $Sales_{it}$, through their association with the endogeneous variable, AR $Usage_{it}$. As realizations of the same variable from different markets can serve as suitable instruments (Papies, Ebbes, and Van Heerde 2017, p. 601), we use the volume of AR usage in two other countries for the same product during the same month as our instruments (i.e., AR $Usage_{it}^{Country\ A}$ and AR $Usage_{it}^{Country\ B}$ respectively). Underlying this choice of instruments is the assumption that customer preferences are similar across markets, and product-specific factors that affect customers' interest in trying products using the AR feature should be constant in all markets, satisfying the first condition. However, the number of customers using the AR feature to try products in other markets should have no bearing on customers' purchase decisions in the focal market, satisfying the second requirement. We also use lagged values of AR $Usage_{it}$ as an alternative instrument (e.g., Danaher et al. 2020), and discuss this further in the robustness analyses section.

Since AR $Usage_{it}$ is a count variable with significant over-dispersion (M = 13.9, SD = 22.7), we used a negative binomial model for the first stage estimation. As predicted residuals from the first stage are used in the estimation of Equation (1), standard errors need to be corrected to account for this additional source of variation (Petrin and Train 2010). We implemented the cluster bootstrapping method (Cameron and Miller 2015, p.327) to approximate the correct standard errors using 1000 bootstrap samples.

Results. From the first stage estimation (provided in Web Appendix D), coefficients for the instruments are positive and significant (.414 for AR Usage$^{\text{Country A}}$ and .301 for AR Usage$^{\text{Country B}}$, $p < .01$ for both). Furthermore, the instruments are highly correlated with AR Usage (.75 for AR Usage$^{\text{Country A}}$ and .64 for AR Usage$^{\text{Country B}}$, $p < .01$ for both), and the F-statistic of excluded instruments in the first stage regression is 5,520, well above the recommended cutoff of 10 (Angrist and Pischke 2009). These results indicate that the instruments are strongly related with the endogeneous variable. To assess validity of the instruments, we performed the Hansen J-test for over-identifying restrictions. Results from the test fail to reject the null hypothesis that the instruments are uncorrelated with the second stage error term (χ^2 (1) = .699, p = .40), providing additional support for the choice of instruments.

To examine the main effect of AR usage in H1, we estimated the second stage model without interaction terms. Results for this model are presented in column (1) of Table 4. The coefficient for AR Usage is significantly positive (.006, $p < .01$), suggesting a small but positive relationship between the number of customers trying the product on AR and sales for the product during the same month. Thus, H1 is supported. The coefficients for other variables are largely in line with common intuition. For example, brand popularity (.894, $p < .05$), breadth of product appeal (.385, $p < .01$), and product rating (.094, $p < .05$) are positively associated with product sales, while price (-.005, $p < .10$) has a negative relationship with product sales. The coefficient for the residual correction term, which is equivalent to the Hausman test for the presence of endogeneity (Papies, Ebbes, and Van Heerde 2017), is significant (.071, $p < .01$), indicating that the endogeneity-corrected estimates are preferred. Thus, we focus on results from the two-stage model, and provide results for the uncorrected model in Web Appendix D.

-------Insert Table 4 here-------

Results for the full second stage model are presented in column (2) in Table 4. In support of H2a and H2b, the interactions between AR Usage and Brand Popularity (-.022, $p <$ .05) and Appeal (-.001, $p < .01$) are significantly negative, indicating that the sales impact of AR usage is stronger for brands that are less popular and products with narrower appeal. The interaction between AR Usage and Price is significantly positive (.000, $p < .10$), suggesting that the sales impact of AR Usage is stronger for products that are more expensive. Thus, H2d is also supported. However, the results do not provide support for H2c, as the interaction between AR Usage and Rating is not significant (.001, $p > .10$).

Robustness analyses. We performed several analyses to ensure that our findings are robust to different assumptions and model specifications. Firstly, following prior research which has used lagged values of endogenous variables as instruments (e.g., Danaher et al. 2020), we used the past 1 month volume of AR usage of product i as an alternative instrument. As app activity data prior to the first month (i.e., Dec 2017) was unavailable, we excluded observations for the first month. Results for this model are presented in column (3), and the findings are consistent. As we are interested to study the moderating effect of ratings, we focused on products that have a rating in the main analysis. Since the coefficient for Rating was not significant, we excluded it in the model specification, and replicated the analysis for all products. Results for this model are also consistent with the main findings, and are presented in column (4).

We also explored alternative operationalizations for AR Usage, Brand Popularity, and Appeal. Instead of operationalizing AR Usage as the number of customers using AR to try product i, we use total AR activity for product i to accommodate repeated AR usage from the same customer. We also operationalize Brand Popularity and Appeal as the number of customers purchasing the brand and product, respectively. Results for these models are reported in Web Appendix E. Across all robustness analyses, results are generally consistent with the main model, providing further validation for our findings.

Category-level Differences-in-differences-in-differences Analysis

The introduction of AR for two eye categories (i.e., eyeshadow and eyeliner) in mid-March 2018 presents a unique opportunity to examine the impact of AR introduction on sales. Using a quasi-experimental approach, we regard AR introduction as a treatment, and examine its impact by comparing differences in sales for products with and without the AR feature, before and after the feature was introduced. Since the AR feature was only available for eyeshadows and eyeliners, a potential comparison could be between these categories and other eye categories that do not have the feature (i.e., eyebrows, mascaras, and eye palettes). This between-category comparison relies on the crucial assumption that sales trends across different eye categories would be parallel in the absence of AR introduction. As cosmetic products are often used concurrently, sales for products targeting the same facial feature should generally move in the same direction. An alternative comparison could be between the app and web channels. This approach avoids the assumption that trends across different eye categories are similar, but requires a separate assumption that without AR introduction, sales trends in the two online channels would be parallel.

A more robust approach that does not require either of these assumptions is the differences-in-differences-in-differences approach (DDD; Wooldridge 2010, p.150; Angrist and Pischke 2009, p. 181), which combines both comparisons. Specifically, the DDD analysis measures differences between app and web sales for eyeshadows and eyeliners before and after AR was introduced, relative to the same differences for other eye categories that do not have the AR feature. Thus, the DDD approach controls for both channel and category trends that could potentially confound the effect, and relies on the more relaxed assumption that before AR was introduced, differences in app vs web sales for eye categories with the AR feature are parallel to differences in app vs web sales for eye categories without the feature. Following Janakiraman, Lim, and Rishika (2018) and Fisher, Gallino, and Xu (2019), we conducted two falsification tests using data from the pre-AR introduction period, and the results provide support that this assumption holds in our study. Details and results for these falsification tests are included in Web Appendix F.

Accordingly, we examine changes in weekly sales for the 5 product categories (i.e., eyeshadow, eyeliner, eyebrows, mascara, and eye palettes) across 2 channels (i.e., app and web) before and after AR was introduced. Our sample covers a duration of 108 weeks (i.e., 42 weeks for the pre-AR introduction period and 66 weeks in the post-AR introduction period), giving us a total of 1,080 observations (5 × 2 × 108 = 1,080).

Model specification. The outcome variable of interest is sales for category j on channel k during week t, Category Sales_{jkt}. As Category Sales_{jkt} is a count variable with significant over-dispersion (M = 64.8, SD = 78.0), we use a negative binomial model for the estimation. Following Wooldridge (2010, p.150), the vector of covariates in the regression is given by:

$$\text{(2)}\quad \mathbf{X_{jkt}\beta} = \beta_0 + \beta_1\text{AR Intro}_t + \beta_2\text{App}_k + \beta_3\text{AR Feature}_j + \beta_4\text{AR Intro}_t \times \text{App}_k \times \text{AR Feature}_j + \beta_5\text{AR Intro}_t \times \text{App}_k + \beta_6\text{AR Intro}_t \times \text{AR Feature}_j + \beta_7\text{App}_k \times \text{AR Feature}_j + \sum_{c=1}^{J-2}\gamma_c\text{Category}_j + \sum_{w=1}^{T-2}\delta_w\text{Week}_t + \varepsilon_{jkt}$$

In Equation (2), AR Intro_t is a dummy variable with a value of 1 if week t is in the post-AR introduction period, and 0 otherwise. App_k is a dummy variable with a value of 1 for the mobile app and 0 for the website, and AR Feature_j is a dummy variable with a value of 1 for eye categories with the AR feature (i.e., eyeshadow and eyeliner) and 0 for other eye categories. The key coefficient of interest is β_4, which captures the three-way interaction between AR introduction, retail channel, and categories that have the AR feature. Thus, β_4

represents the additional change in mobile app sales post-AR introduction for eyeshadow and eyeliner, after accounting for channel and category-related changes over the same period (captured by β_5 and β_6 respectively). We include all lower-order interactions in the model, as well as a series of dummy variables, Category_j (for j = 1,…,J categories) and Week_t, (for t = 1,…,T weeks) to control for category and week effects. Since Category_j is perfectly collinear with AR Feature_j and Week_t is perfectly collinear with AR Intro_t, we excluded dummy variables for an additional category and week. To account for the panel nature of the data, standard errors are clustered at the category-channel level, allowing errors for observations from the same category within each channel to correlate.

Results. Before discussing results for the DDD analysis, we present the basic pre-post model in column (1) of Table 5. We regress weekly mobile app sales for eyeshadow and eyeliner on AR Intro_t and the vector of dummies. The coefficient for AR Intro_t is significantly positive (.611, $p < .05$), providing preliminary evidence that sales increased after AR was introduced. Results for the DDD analysis are presented in column (2) of Table 5. The coefficient for the three-way interaction between AR introduction, app, and categories with the AR feature is marginally significant (.449, $p < .10$), providing some evidence that sales for eyeshadows and eyeliners increased on the app channel after AR was introduced.

-------Insert Table 5 here-------

Robustness analyses. To check the DDD identification strategy, we included channel and category trends to Equation (2) (Angrist and Pischke 2009, p. 178). Results of this alternative model are presented in column (3), and the coefficient of the three-way interaction of interest is similar in direction, magnitude and significance with the main model. While the weekly fixed effects control for variations in overall sales between weeks, they do not account for time-varying confounding effects that are specific to the channel-category. Thus, if there are more app-exclusive sale events for the eyeshadow and eyeliner categories in the post-AR introduction period relative to the pre-AR introduction period, the effect of AR Introduction on app sales in these two categories would be overstated. As a robustness check, we removed weeks that coincide with sale events from the analysis, and present the results in column (4) of Table 5. We also split AR $Feature_j$ into the two eye categories with the AR feature, $Eyeshadow_j$ and $Eyeliner_j$, and the coefficients of both three-way interactions are marginally significant, providing convergent validity for our results. Furthermore, results from the Wald test for equality of coefficients fail to reject the null hypothesis that the coefficients are the same (p = .76), indicating that the effect of AR introduction on sales is not product-specific. Lastly, we estimate the same model using a Poisson regression. Results of these additional analyses are provided in Web Appendix G. Across all robustness analyses, the direction, magnitude, and significance of coefficients are similar to the main model.

Overall, the results provide additional support for H1, and demonstrate that the positive impact of AR generalizes to other product categories. We note that as the retailer did not announce the introduction of AR for the eye categories, usage of the feature was low. On average, the weekly number of customers using AR to try products from the eye categories is 6.4 times lower than the number for lip categories (M_{Eyes} = 271.14 vs. M_{Lips} = 1,737.00). Thus, our result is a conservative estimate of the impact of AR introduction, and we speculate that the effect could be larger had the feature been advertised. To establish a direct relationship between AR usage and purchase, and further examine the moderating effects of customers' channel and category experience, we turn our attention to the customer-level.

Customer-level Analysis

We focus on the sample of active customers (i.e., made a purchase in the past 1 year) who browsed products in the eyeshadow or eyeliner categories during the 12-month period[2]

[2] We also repeat the analysis for the 3 and 6-month period, and discuss insights from these analyses in the results section.

after AR was introduced for these two categories (i.e., mid-March 2018 to mid-March 2019). In total, our sample comprises of 42,493 customers. At the time of AR introduction, 40.2% of these customers had never purchased online before (i.e., new to online channel) and 43.4% had never purchased eyeshadow or eyeliner before (i.e., new to the categories). During the 12-month period after the AR feature was introduced for the two categories, 13.9% of customers used the feature to try eyeshadows and eyeliners, and 15.0% purchased at least one product from these categories on the app. Accordingly, we model how AR usage influences customers' probability of purchasing products from these two categories in the focal period.

Model specification. The dependent variable of interest, $P(\text{Purchase}_i^{\text{Eyes}})$, is customer i's probability of purchasing at least one eyeshadow or eyeliner on the app within 12 months after AR was introduced for the two categories. As the dependent variable is binary, we used a probit model with the following specification:

$$\text{(3)} \quad P(\text{Purchase}_i^{\text{Eyes}} = 1 | X_i\beta) = \Phi\,(\beta_0 + \beta_1\,\text{AR Usage}_i^{\text{Eyes}} + \beta_2\,\text{New Channel}_i + \beta_3\,\text{New Category}_i + \beta_4\,\text{AR Usage}_i^{\text{Eyes}} \times \text{New Channel}_i + \beta_5\,\text{AR Usage}_i^{\text{Eyes}} \times \text{New Category}_i + \mathbf{Browsing}_i'\boldsymbol{\gamma} + \mathbf{Past\ Purchase}_i'\boldsymbol{\delta} + \varepsilon_i)$$

In Equation (3), Φ denotes the standard probit link function. $\text{AR Usage}_i^{\text{Eyes}}$ represents the focal independent variable and takes a value of 1 if customer i used the AR feature to try eyeshadows or eyeliners during the period, and 0 otherwise. New Channel_i and New Category_i are both indicator variables representing customers' (lack of) prior experience with the channel and category. New Channel_i takes a value of 1 if customer i is new to the online channel, and 0 otherwise, while New Category_i takes a value of 1 if customer i is new to the two eye categories, and 0 otherwise. To examine how these two variables moderate the effect of AR usage on purchase, we included interactions between the variables and $\text{AR Usage}_i^{\text{Eyes}}$. We also included a vector, $\mathbf{Browsing}_i$, to control for customers' browsing behavior before and during the focal period to account for customer interest and engagement. As the browsing activity dataset starts from December 2017 (i.e., 3 months prior to the introduction of AR for the eye categories), we used a 3-month window for past browsing behavior. Lastly, we included a vector, **Past Purchase$_i$**, to control for customers' purchase history in the 12 months prior to AR introduction to account for customer loyalty. Table 6 provides a summary of how the variables are operationalized and their descriptive statistics. The correlations are provided in Web Appendix H, and the variance inflation factors (VIF) are below 1.75, indicating that multi-collinearity is not an issue.

-------Insert Table 6 here-------

Identification strategy. As customers who already intend to purchase products may be more likely to try them using the AR feature, we use the two-stage residual inclusion method to account for this self-selection bias. We use customers' past AR usage for lip products (prior to introduction of the feature for the eye categories) as the instrument. Since introduction of AR for the eye categories was not announced, customers who have not used the feature before may be unaware of it, and have a lower likelihood of using the feature. Conversely, customers who have used AR to try lip products in the past should have a higher likelihood of using it again for eye products, as they are already aware of this feature. Furthermore, since lip and eye products target different areas of the face, past usage of the AR feature to try lip products should not have a direct impact on the probability of purchasing eye products during the focal period. Thus, we included Past AR Usage$_i^{Lips}$ as an instrument in the first stage to estimate customer i's likelihood of using AR in the focal period. The variable is coded as 1 if customer i used the AR feature to try lip products in the 3 months before AR was introduced for the eye categories, and 0 otherwise. Residuals from the first-stage estimation are then included in Equation (3) to estimate P(Purchase$_i^{Eyes}$). Similar to the product model, we bootstrapped 1000 samples to obtain the proper standard errors. To examine if the findings are robust to alternative identification strategies, we also adopted the propensity score weighting approach, which does not rely on instruments. We discuss this further in the robustness analyses section.

Results. The coefficient of the instrument in the first stage estimation (provided in Web Appendix I) is positive and significant (.176, $p < .01$), and the F-statistic of excluded instrument in the first stage regression is 15.8, providing evidence for the strength of the instrument. However, the coefficient for the residual correction term, which is equivalent to the Hausman test for the presence of endogeneity (Papies, Ebbes, and Van Heerde 2017), is not significant, suggesting that endogeneity may not be a concern. We also used the Heckman selection method (Heckman 1979) as an alternative identification strategy, and the inverse Mills ratio is similarly not significant. Hence, we report estimates for the uncorrected model in the results section, and provide the full result for both the two-stage residual inclusion and Heckman selection methods in Web Appendix I. We note that across all models, the substantive findings of interest remain consistent.

Column (1) of Table 7 displays the results for the model without interactions, representing factors influencing purchase of eyeshadows or eyeliners during the 12 months after AR was introduced. The coefficient of AR Usage^{Eyes}, is positive and significant (.046, $p < .05$), providing further evidence for H1. The coefficients of other variables are largely in line with expectations. For example, the coefficient for New Channel (-.329, $p < .01$) and New Category (-.120, $p < .01$) are significantly negative, indicating that customers who are new to the online channel or product category are less likely to make a purchase. The number of orders (.007, $p < .01$), average order value (.002, $p < .01$), and number of eye products purchased in the past (.080, $p < .01$) are positively related to probability of purchasing eye products. Furthermore, total browsing duration (.000, $p < .01$) and number of eye product pages viewed (.007, $p < .01$) are also positively related to the purchase of eye products.

-------Insert Table 7 here-------

Column (2) of Table 7 provides results for the 12-month model, including interactions. The interaction between AR Usage^{Eyes} and New Channel is positive and significant (.091, $p < .05$), suggesting that AR has a stronger effect among customers who have never purchased online before. The average marginal effect of AR usage for customers who are new to the online channel is significantly positive (.018, $p < .01$), but not significant for existing online customers (.004, $p = .59$). Thus, H3a is supported. While the interaction between AR Usage^{Eyes} and New Category is marginally significant (.082, $p < .10$), the average marginal effect of AR usage is significantly positive for customers who are new to the product category (.019, $p < .01$), and not significant for existing category customers (.003, $p = .65$), providing support for H3b as well.

To understand how the impact of AR changes over time, we repeated the same analysis using a 6-month and 3-month window, presented in column (3) and (4) of Table 7. We find that the interactions between AR Usage^{Eyes} with New Channel and New Category become stronger over time – while both interactions (as well as the average marginal effects) are insignificant in the 3-month period, the interaction with New Channel becomes significant in the 6 and 12-month period, and the interaction with New Category becomes marginally significant in the 12-month period. Similar to the 12-month model, the average marginal effects in the 6-month model are significantly positive for customers who are new to the online channel (.022, $p < .01$, versus .006, $p = .44$ for existing online customers) and product category (.019, $p < .05$, versus .007, $p = .31$ for existing category customers). These results suggest that customers may require some time to become comfortable with the technology before using it to make purchase decisions. Additionally, the results also imply that the impact of AR does not wear out over time, and rule out novelty effect as an alternative explanation.

Robustness analyses. Results for the 2-stage residual inclusion and Heckman selection methods for all 3, 6, and 12-month periods are provided in Web Appendix I. To further examine if the findings are robust to alternative identification strategies, we applied the propensity score weighting approach. We use the first stage equation to calculate customers' propensity of using AR in the focal period, and include this as weights in the estimation of Equation (3), following Bell, Gallino, and Moreno (2018). The results are consistent with the main model, and are also reported in Web Appendix I.

We also examine if the findings are robust to alternative variable operationalizations. Firstly, instead of the probability of purchasing eye products, we use the number of eye products purchased during the focal period as an alternative dependent variable. Secondly, we replace the binary AR Usage variable with the number of sessions involving AR usage during the focal period. Thirdly, as alternative measures of channel and category experience, we use the number of online transactions and number of eye products purchased prior to AR introduction, respectively. Findings from these models are consistent, and the results are presented in Web Appendix J.

Discussion

While firms are keen to invest in AR, research demonstrating its impact in real-world contexts is limited. The present research provides some preliminary confirmation that the availability and usage of AR have a positive impact on sales, although the overall impact appears to be small. Taken together, our findings provide converging evidence that AR is most effective when product-related uncertainty is high, indicating that uncertainty reduction could be a possible mechanism for AR to improve sales. Nevertheless, we do not find a significant moderating effect for product ratings, suggesting that even though AR may reduce product fit uncertainty, it may still be unable to compensate for the higher performance uncertainty associated with products that have lower ratings[3]. While we have adopted instrumental variable and quasi-experimental approaches to address endogeneity that is inherent in observational data, we acknowledge that these findings should be viewed as evidence based on correlations, with attempts to come close to causality.

Research Implications

*Augmented Reality and product preference***.** Complementing past research that have explored how website features drive sales for niche products (e.g., Brynjolfsson, Hu, and Simester 2011; Tucker and Zhang 2011), our research shows that AR can increase preference for products or brands that are less popular. Thus, retailers carrying wide product assortments can use AR to stimulate demand for products at the long tail of the sales distribution. AR may also help to level the playing field for less-popular brands. With the launch of AR-enabled display ads on advertising platforms such as Facebook and YouTube, less-established brands could consider investing in this new ad format, as they stand to benefit most from this technology. Retailers selling premium products may also leverage AR to improve decision comfort and reduce customers' hesitation in the purchase process.

Augmented Reality and category sales. We find that the impact of AR is stronger for customers who are new to the category, suggesting that AR could increase sales via category expansion. However, as AR seems to be most effective when the level of uncertainty is high, its impact may diminish over time as customers become more familiar with the product category and experience less uncertainty[4]. Nevertheless, the finding that AR has a stronger impact for products that are more expensive suggests that beyond increasing unit sales, AR

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[3] We thank an anonymous reviewer for suggesting this possible explanation for the lack of significant result to support H2c.
[4] We thank an anonymous reviewer for highlighting this possibility, and encourage future research to explore the dynamic effects of AR usage.

can also improve category revenues by encouraging customers to purchase products with wider margins. Thus, investments to deploy AR in retail could pay off in the long run.

Augmented Reality and channel choice. Compared to existing online customers, we find that AR has a stronger effect for customers who are new to the online channel. As prior research has shown that multichannel customers are more profitable (Montaguti, Neslin, and Valentini 2016), omni-channel retailers can use AR to encourage their offline customers to adopt the online channel. Given that AR increases online sales among customers who are new to the channel, a potential concern is that AR could lead to cannibalization of sales from offline channels. To understand if the increase in app purchases is coming at the expense of other sales channels, we ran the same model in Equation (3), but replaced the dependent variable with the probability of purchasing eye products in the web and offline channels (results reported in Web Appendix K). We did not find evidence to indicate that offline customers who use AR (on the app) are more likely to purchase from the web, suggesting that the impact of AR is specific to the app platform. Interestingly, we find that offline customers who use AR are more likely to purchase from the offline channel in the 3-month model, but not in the 6 and 12-month model. Thus, contrary to our expectations, the results suggest that AR could have a positive spillover effect to the offline channel, at least in the short run.

An Agenda for Future Research

Complementing prior research, which has predominantly studied AR from a consumer perspective, our research extends the literature by examining what AR means for retailers. To encourage the academic community to produce more impactful research in this nascent field, we developed a research agenda for AR in marketing, with an emphasis on identifying research topics that have strong managerial relevance for industry practitioners. Based on a review of the academic literature (e.g., Wedel, Bigné, and Zhang 2020) and recent advancements of the AR technology, we generated a list of potential research topics, and synthesized these topics into five themes. Next, we consulted two senior marketing practitioners and two academics with expertise in this area to review the research themes and associated topics, and refined the list based on their feedback.

To determine the practical importance of each research theme, we conducted an online survey with 36 marketing practitioners from companies that are currently using (or planning to use) AR in their marketing, advertising, or retailing activities. Survey respondents first independently rated each research theme in terms of importance to business performance (see Stremersch and Van Dyck 2009), before ranking the five research themes from most to least important. To avoid primacy and recency effects, the order of research themes was randomized across respondents. The mean rating (ranging from 5.1 to 5.8 on a 7-point scale) and ranking scores (from 1st to 5th; lower number reflects higher importance) are inversely proportional, demonstrating internal consistency. Web Appendix L provides details for the survey, including survey design, respondent recruitment, and background of respondents.

Table 8 presents the research agenda for AR in marketing, comprising the five research themes (ordered by practical importance) and potential topics that could be explored under each theme. Given the novelty of the technology, marketers are primarily concerned with how different design features could be configured to create more effective AR experiences for consumers. For example, greater clarity is needed regarding factors that affect AR experiences, such as fidelity (i.e., how closely virtual objects resemble real objects), motion (i.e., static vs. animated virtual objects), spatial presence (i.e., the feeling that virtual objects exist in a physical space), and embodiment (i.e., the ability to use bodily movements to control virtual objects), and how they can be delivered on AR interfaces. Beyond visual and auditory senses, how haptic feedback (e.g., emission of vibrations on devices to stimulate the sense of touch) influences AR experiences is also of interest.

-------Insert Table 8 here-------

Another important consideration is how AR fits into companies' overall marketing strategy. Specifically, marketers would like to know how they can better integrate AR at different stages of the customer journey to increase brand engagement, build emotional connections, and improve relationships with customers. There is also ambiguity regarding the synergy between AR and other marketing communications mix (e.g., advertising, sales promotions), as well as the effectiveness of product placements and pop-up stores in AR-enabled virtual environments. In particular, the potential for this new technology to complement or replace existing communication and retail channels is still uncertain. As most recent applications of AR have focused on consumer products, marketers also need more guidance on how AR can be appropriately deployed in service industries, such as the tourism and hospitality sector.

Besides these two key areas, other worthwhile avenues to explore include the impact of AR on consumer behavior (e.g., cognitive functions, rational decision-making, and brand perceptions), how marketers can promote wider adoption of AR, and how the technology can be used to generate valuable marketing insights. Although our research agenda focuses on AR, we note that the research themes could be broadened to encompass other extended realities (i.e., Virtual Reality and Mixed Reality).

In conclusion, we believe that the marketing community would benefit from a deeper investigation of virtual experiences and their role in marketing. We are excited about where this field is heading, and look forward to more insightful research to reinforce our understanding of the profound impacts of these new technologies in the marketing domain.

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Tables & Figures

TABLE 1. USES OF AR IN RETAIL

Uses of AR	Role of AR	Illustrative Use Cases
Entertain customers	• Create novel and engaging experiences for customers • Build brand interest • Drive foot traffic to physical stores	• Walmart collaborated with DC Comics and Marvel to bring exclusive superhero-themed AR experiences to selected outlets. • Starbucks Reserve Roastery in Shanghai uses AR to offer customers a digital tour of their massive roasting facility.
Educate customers	• Deliver content and information in an interactive and visually appealing manner • Help customers understand complex mechanisms and better appreciate the value of products	• Walgreen and Lowe's use AR in their in-store navigation apps to guide users to product locations, and notify them if there are special promotions along the way. • Toyota and Hyundai use AR to demonstrate key features and innovative technologies in their new car models.
Help customers ***Evaluate*** product fit	• Help customers visualize products in their actual consumption contexts • Increase customers' confidence in their purchase decisions in the absence of physical products • Accommodate wide product assortments and customization without the need for physical inventory	• Ikea's Place app uses AR to help customers determine if products fit with their existing room décor. • L'Oréal's Virtual Try-On feature and Sephora's Virtual Artist app use AR to show customers how different cosmetic products would look on them. • Uniqlo and Topshop use AR to offer a more convenient way of trying different outfits in their physical stores. • BMW and Audi use AR to give customers a preview of cars based on customized features such as paint color, wheel design, and interior aesthetics.
Enhance customers' post-purchase consumption experience	• Offer new ways of enjoying products after they are purchased • Deliver additional information while the products are being used or consumed	• Lego's Hidden Side sets are specially designed to be played with the companion AR app. • McDonald's used AR to let customers discover the origins of ingredients in the food they purchased. • Hyundai's Virtual Guide app uses AR to teach car owners how to perform basic maintenance.

Notes: URL links to examples given are provided in Web Appendix B.

TABLE 2. SELECTED LITERATURE ON AR IN RETAIL

Paper	Methodology	Context	Key Outcome Variables	Key Findings
Hilken et al. (2017)	Experimental	Using situated cognition theory to understand AR's potential to enhance online experiences	Value perceptions of online experiences; decision comfort; purchase and word-of-mouth intentions	• The combination of simulated physical control and environmental embedding offered by AR creates a feeling of spatial presence. • As a result, AR enhances perceptions of online experiences, decision comfort, and behavioral intentions.
Yim, Chu, and Sauer (2017)	Experimental	Comparing AR vs web-based product presentation	Attitude towards AR and purchase intentions	• Compared to web-based displays, AR is more immersive due to its interactive and vivid nature. • As a result, AR is perceived to be more useful and enjoyable, leading to positive attitudes and purchase intentions.
Brengman, Willems, and Van Kerrebroeck (2019)	Experimental	Impact of AR on perceived ownership	Perceived ownership and purchase intentions	• Compared to other touch and non-touch interfaces, mobile-enabled AR creates higher feelings of perceived ownership, positively impacting attitude and purchase intentions.
Heller et al. (2019a)	Experimental	Using mental imagery theory to understand how AR influences word-of-mouth	Word-of-mouth intentions	• AR improves processing fluency by facilitating imagery generation and transformation, leading to higher decision comfort and word-of-mouth intentions.
Heller et al. (2019b)	Experimental	Comparing touch vs. voice control modalities in multi-sensory AR	Decision comfort and willingness to pay	• Touch control (vs voice control) reduces mental intangibility, leading to higher decision comfort and willingness to pay.
Hilken et al. (2020)	Experimental	Shared decision-making using social AR	Decision-makers' product choice; spillover effects to recommenders	• AR empowers recommenders by allowing them to take the point of view of the decision-makers. • AR stimulates recommenders' desire for products, leading to positive behavioral intentions.
Current paper	Instrumental variable estimation and quasi-experiment using real-world data	Examining the impact of AR usage on sales, and the moderating impact of product and customer characteristics	Product and category sales	• AR has a positive impact on sales for brands that are less popular, products with narrower appeal, and products that are more expensive. • AR has a stronger impact for customers who are new to the retailer's online channel or product category.

TABLE 3. VARIABLE OPERATIONALIZATION & DESCRIPTIVE STATISTICS FOR PRODUCT MODEL

Variable	Operationalization	Mean	SD	Min	Median	Max
1. Product Sales	Total product sales from mobile app (in units)	.46	1.73	.00	.00	64.00
2. AR Usage	Number of customers using AR to try the product in focal country	13.90	22.67	.00	6.00	611.00
3. AR Usage^{Alt}	Number of AR activity for the product in focal country	14.45	23.92	.00	7.00	620.00
4. Brand Popularity	Total brand sales from website (in thousands of units)	.04	.07	.00	.02	.51
5. Brand Popularity^{Alt}	Number of customers buying the brand from website (in thousands)	.03	.04	.00	.01	.42
6. Appeal	Total product sales from website (in units)	.25	.97	.00	.00	32.00
7. Appeal^{Alt}	Number of customers buying the product from website	.25	.95	.00	.00	31.00
8. Rating	Product rating at time t (on a 5-point scale)	4.14	.67	.50	4.25	5.00
9. Price	Product price at time t	31.80	11.17	5.00	32.00	77.00
10. AR Usage$^{Country\ A}$	Number of customers using AR to try the product in country A	.59	1.43	.00	.00	39.00
11. AR Usage$^{Country\ B}$	Number of customers using AR to try the product in country B	.28	.71	.00	.00	11.00

TABLE 4. PRODUCT MODEL: IMPACT OF AR USAGE ON PRODUCT SALES & MODERATING EFFECTS OF PRODUCT CHARACTERISTICS

	Column (1) Second Stage (Without Interactions)			Column (2) Second Stage (Full Model)			Column (3) Past 1 Month AR Usage as Alternative Instrument			Column (4) Including Products Without Ratings		
H1: AR Usage	**.006**	**(.001)**	***	-.002	(.006)		-.003	(.007)		.007	(.006)	
Brand Popularity	.894	(.364)	**	1.482	(.356)	***	1.796	(.396)	***	1.675	(.333)	***
Appeal	.385	(.029)	***	.416	(.023)	***	.419	(.027)	***	.473	(.023)	***
Rating	.094	(.042)	**	.052	(.054)		.062	(.056)		-		
Price	-.005	(.003)	*	-.009	(.004)	**	-.008	(.004)	**	-.010	(.003)	***
H2a: AR Usage × Brand Popularity	-			**-.022**	**(.009)**	**	**-.025**	**(008)**	***	**-.028**	**(.010)**	***
H2b: AR Usage × Appeal	-			**-.001**	**(.000)**	***	**-.001**	**(.000)**	**	**-.001**	**(.000)**	***
H2c: AR Usage × Rating	-			**.001**	**(.001)**		**.001**	**(.001)**		-		
H2d: AR Usage × Price	-			**.000**	**(.000)**	*	**.000**	**(.000)**	*	**.000**	**(.000)**	*
Correction Term	.071	(.027)	***	.050	(.027)	*	.102	(.053)	*	.063	(.026)	**
Constant	-1.114	(.223)	***	-.913	(.264)	***	-1.185	(.280)	***	-.687	(.162)	***
Category dummy	Included			Included			Included			Included		
Month dummies	Included			Included			Included			Included		
Observations	29,345			29,345			28,305			44,346		
Log Likelihood	-18,573			-18,517			-17,630			-25,310		

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

Notes: Standard errors (clustered at product level) in parentheses

TABLE 5. DDD ANALYSIS: IMPACT OF AR INTRODUCTION ON CATEGORY SALES

	Column (1) Basic Pre-Post Model	Column (2) DDD Analysis	Column (3) Including Channel and Category Trends	Column (4) Excluding Sale Events
AR Intro	**.611 (.245) ****	.265 (.214)	.771 (.445) *	.720 (.429) *
App	-	.125 (.058) **	39.187 (9.72) ***	31.953 (8.95) ***
AR Feature	-	.068 (.146)	5.794 (8.44)	3.720 (7.57)
AR Intro × App × AR Feature	-	**.449 (.262)** *	**.441 (.249)** *	**.465 (.264)** *
AR Intro × App	-	-.601 (.237) **	.243 (.154)	.036 (.169)
AR Intro × AR Feature	-	-.155 (.177)	-.066 (.209)	-.113 (.200)
App × AR Feature	-	-.034 (.088)	-.027 (.056)	-.036 (.048)
Constant	2.043 (.040) ***	2.604 (.156) ***	2.403 (.226) ***	2.464 (.201) ***
Category dummies	Included	Included	Included	Included
Week dummies	Included	Included	Included	Included
Category trend	Not Included	Not Included	Included	Included
Channel trend	Not Included	Not Included	Included	Included
Observations	216	1,080	1,080	940
Log Likelihood	-897	-5,143	-5,095	-4,179

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

Notes: Standard errors (clustered at category-channel level) in parentheses

TABLE 6. VARIABLE OPERATIONALIZATION & DESCRIPTIVE STATISTICS FOR CUSTOMER MODEL

Variable	Operationalization	Mean	SD	Min	Median	Max
1. Purchase^{Eyes} (1/0)	1 if customer bought eye products in the focal period, 0 otherwise	.15	.36	.00	.00	1.00
2. AR Usage^{Eyes} (1/0)	1 if AR was used to try eye products in the focal period, 0 otherwise	.14	.35	.00	.00	1.00
3. New Channel (1/0)	1 if customer has never purchased online before the focal period, 0 otherwise	.40	.49	.00	.00	1.00
4. New Category (1/0)	1 if customer has never purchased eye products before the focal period, 0 otherwise	.43	.50	.00	.00	1.00
Browsing controls						
5. Past Duration	Total browsing duration in the past 3 months (in minutes)	11.56	25.60	.00	.00	150.18
6. Past Pages^{Eyes}	Number of eye product pages viewed in the past 3 months	.77	2.90	.00	.00	23.00
7. Past AR Usage^{Lips} (1/0)	1 if customer has used AR for lip products in the past 3 months, 0 otherwise	.02	.15	.00	.00	1.00
9. Duration	Total browsing duration in the focal period (in minutes)	153.17	148.32	2.82	106.57	1054.25
8. Pages^{Eyes}	Number of eye product pages viewed in the focal period	19.21	24.98	1.00	9.00	128.00
Purchase controls						
10. Past Order Number	Number of transactions in the past 1 year	6.92	5.83	1.00	5.00	37.00
11. Past Order Value	Average value of transactions in the past 1 year	81.88	50.49	.00	70.68	547.00
12. Past Eye Purchases	Number of eye products purchased in the past 1 year	.89	1.50	.00	.00	11.00
13. Recent Order	Number of months from the most recent transaction	2.64	2.49	.03	2.03	12.13
14. First Order	Number of months from the first transaction	18.92	7.73	.03	22.37	26.80

Notes: "Eye products" refers to eyeshadow and eyeliner, the two categories of interest. The focal period is 12 months after AR was introduced for eye products (i.e., March 15, 2018 to March 15, 2019).

TABLE 7. CUSTOMER MODEL: IMPACT OF AR USAGE ON PROBABILITY OF PURCHASE & MODERATING EFFECTS OF CUSTOMER CHARACTERISTICS

	Column (1) 12-Month Model (Without Interactions)	**Column (2) 12-Month Model (Full Model)**	**Column (3) 6-Month Model (Full Model)**	**Column (4) 3-Month Model (Full Model)**
H1: AR Usage^{Eyes}	**.046 (.022) ****	-.015 (.030)	.004 (.047)	-.036 (.084)
New Channel	-.329 (.018) ***	-.344 (.019) ***	-.323 (.029) ***	-.296 (.040) ***
New Category	-.121 (.020) ***	-.134 (.021) ***	-.060 (.032) *	-.122 (.042) ***
H3a: AR Usage^{Eyes} × New Channel	**-**	**.091 (.046) ****	**.144 (.070) ****	**.091 (.138)**
H3b: AR Usage^{Eyes} × New Category	**-**	**.082 (.045) ***	**.075 (.068)**	**-.004 (.135)**
Past Duration	-.002 (.000) ***	-.002 (.000) ***	-.002 (.000) ***	-.002 (.000) ***
Past Pages^{Eyes}	-.003 (.003)	-.003 (.003)	.000 (.002)	-.004 (.002) **
Duration	.000 (.000) ***	.000 (.000) ***	.001 (.000) ***	.001 (.000) ***
Pages^{Eyes}	.007 (.000) ***	.007 (.000) ***	.008 (.000) ***	.017 (.001) ***
Past Order Number	.007 (.002) ***	.007 (.002) ***	.005 (.003)	.003 (.004)
Past Order Value	.002 (.000) ***	.002 (.000) ***	.002 (.000) ***	.002 (.000) ***
Past Eye Purchases	.080 (.006) ***	.081 (.006) ***	.103 (.012) ***	.062 (.011) ***
Recent Order	-.019 (.004) ***	-.020 (.004) ***	-.020 (.006) ***	-.016 (.008) *
First Order	-.001 (.001)	-.001 (.001)	-.002 (.002)	.005 (.002) *
Constant	-1.285 (.035) ***	-1.276 (.035) ***	-1.567 (.054) ***	-1.771 (.077) ***
Observations	42,493	42,493	24,147	13,434
Log Likelihood	-16,614	-16,609	-7,423	-3,773

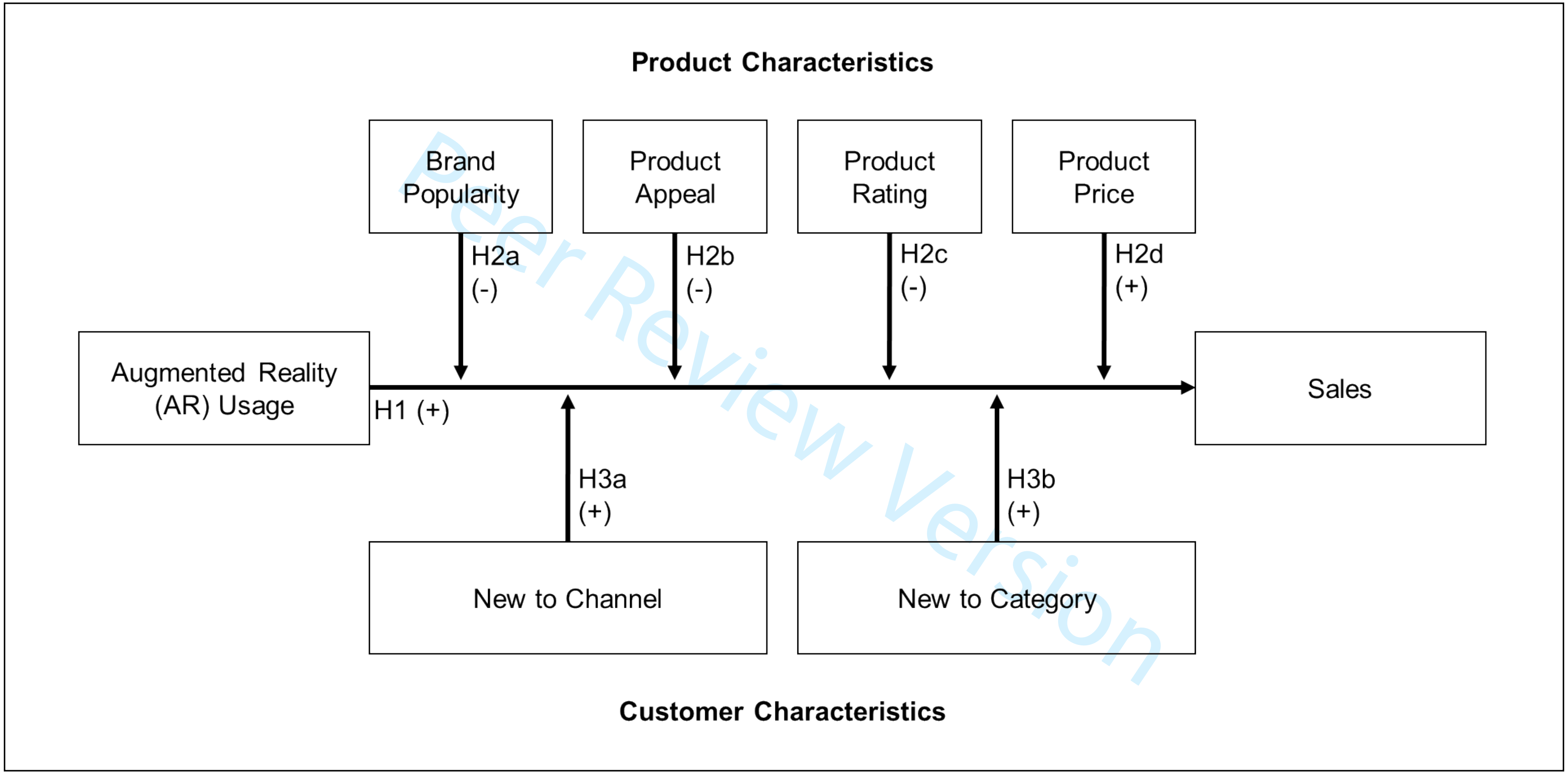
* $p \leq .10$; ** $p \leq .05$; *** $p \leq .01$
Notes: Standard errors in parentheses

TABLE 8. RESEARCH AGENDA FOR AR IN MARKETING

Research Themes	Potential Research Topics
Designing Effective AR Experiences *Rating: 5.81* *Ranking: 2.14*	• How factors such as fidelity (i.e., how closely virtual objects resemble real objects), motion (i.e., static vs. animated virtual objects), spatial presence (i.e., the feeling that virtual objects exist in a physical space), and embodiment (i.e., the ability to use bodily movements to control virtual objects) affect AR experiences. • How the incorporation of senses such as haptic feedback (e.g., emission of vibrations) influence AR experiences. • How content and other elements in the virtual environment could be personalized to enhance AR experiences and influence behavior.
AR and Marketing Strategy *Rating: 5.50* *Ranking: 2.78*	• How marketers can use AR more effectively at different stages of the customer journey to increase brand engagement and improve relationships with customers. • Synergy between AR and other marketing communications mix (e.g., advertising, sales promotions). • Effectiveness of product placements and pop-up stores in AR-enabled virtual environments, and their potential to complement or replace physical stores. • How AR can be deployed in service industries (e.g., tourism and hospitality, F&B retail).
AR and Consumer Behavior *Rating: 5.22* *Ranking: 3.06*	• How AR experiences affect sensory perceptions and cognitive functions (e.g., attention, information processing, learning, and memory). • How AR experiences affect rational decision-making (e.g., product selection strategies; relative importance of attributes) and irrational tendencies (e.g., psychological ownership). • The role of AR experiences in attitude formation and brand perceptions. • How AR experiences affect purchase behaviors and post-purchase product evaluations.
Promoting AR Adoption *Rating: 5.22* *Ranking: 3.42*	• Barriers to using AR technologies (e.g., awkwardness of using it in public; privacy and security concerns; lack of realism in virtual environments), and how marketers can overcome these barriers to encourage wider adoption. • How delivery of the AR experience and advancements in high-tech devices (e.g., 3D depth camera technology; wearable AR glasses) influence consumers' acceptance and usage of the technology. • How offline contextual factors (e.g., distance to physical stores; private vs public space) affect AR usage.
AR as a Marketing Intelligence Tool *Rating: 5.11* *Ranking: 3.61*	• How AR experiences could be used to generate insights for new product development, assortment planning, and store layout / design. • New behavioral data (e.g., motion, interactions within virtual environments) that could be obtained from AR platforms, and how they can be used to measure / predict consumers' responses or decision-making processes. • Privacy and security concerns regarding behavioral data collected on AR platforms, and what marketers can do to reduce these concerns.

Notes: Research Themes are ordered by importance based on a survey with 36 marketing practitioners. Details of the survey are provided in Web Appendix L. "Rating" refers to the mean importance rating score (on a 7-point scale). "Ranking" refers to the mean importance ranking (from 1st to 5th; lower number reflects higher importance).

FIGURE 1. CONCEPTUAL FRAMEWORK



Augmented Reality in Retail and its Impact on Sales

Web Appendix

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WEB APPENDIX A: ADDITIONAL FIGURES

Figure A1. Examples of Augmented Reality in Retail

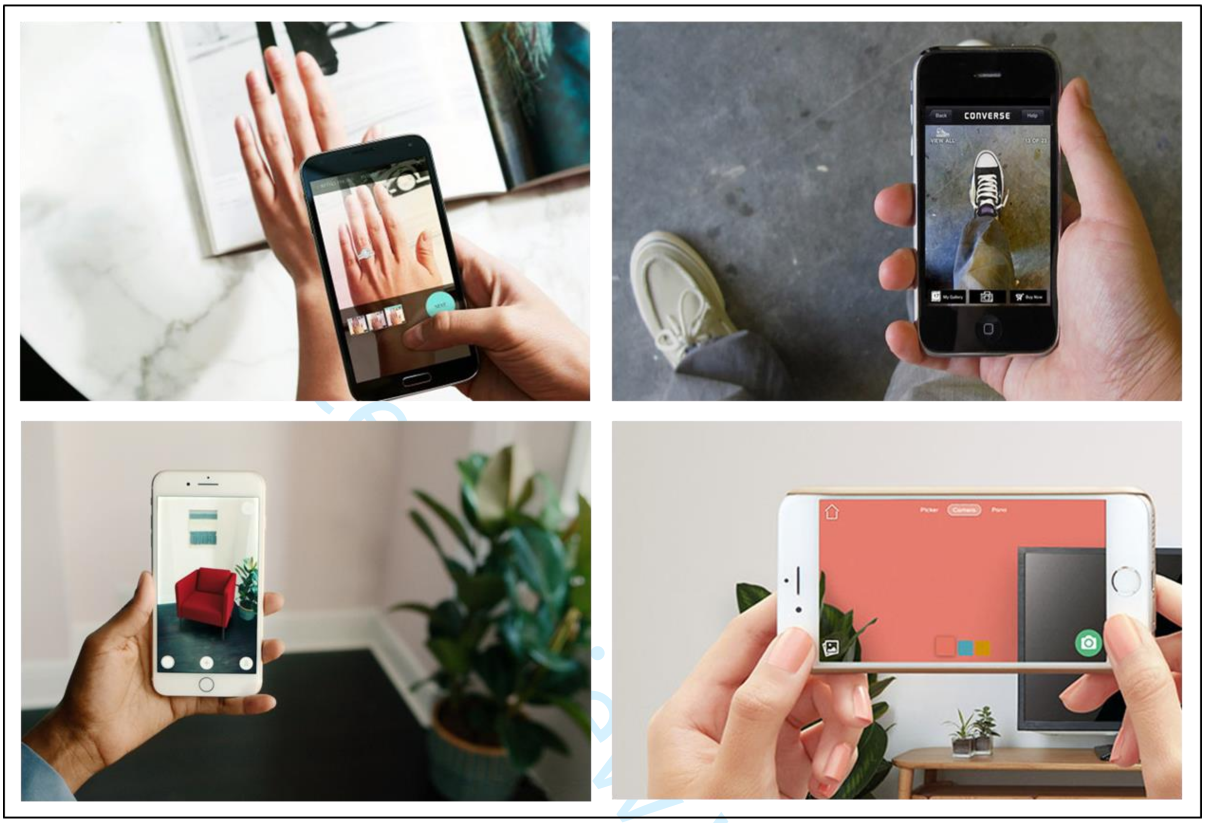


Figure A2. Augmented Reality vs Virtual Reality

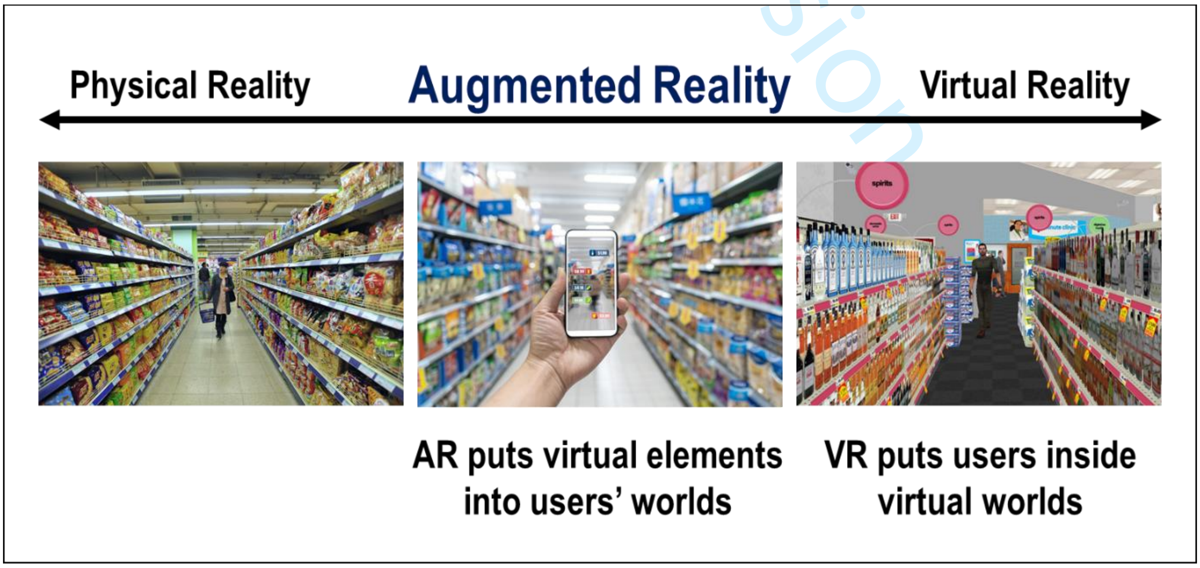


Figure A3. Example of Product Exposure on Mobile App

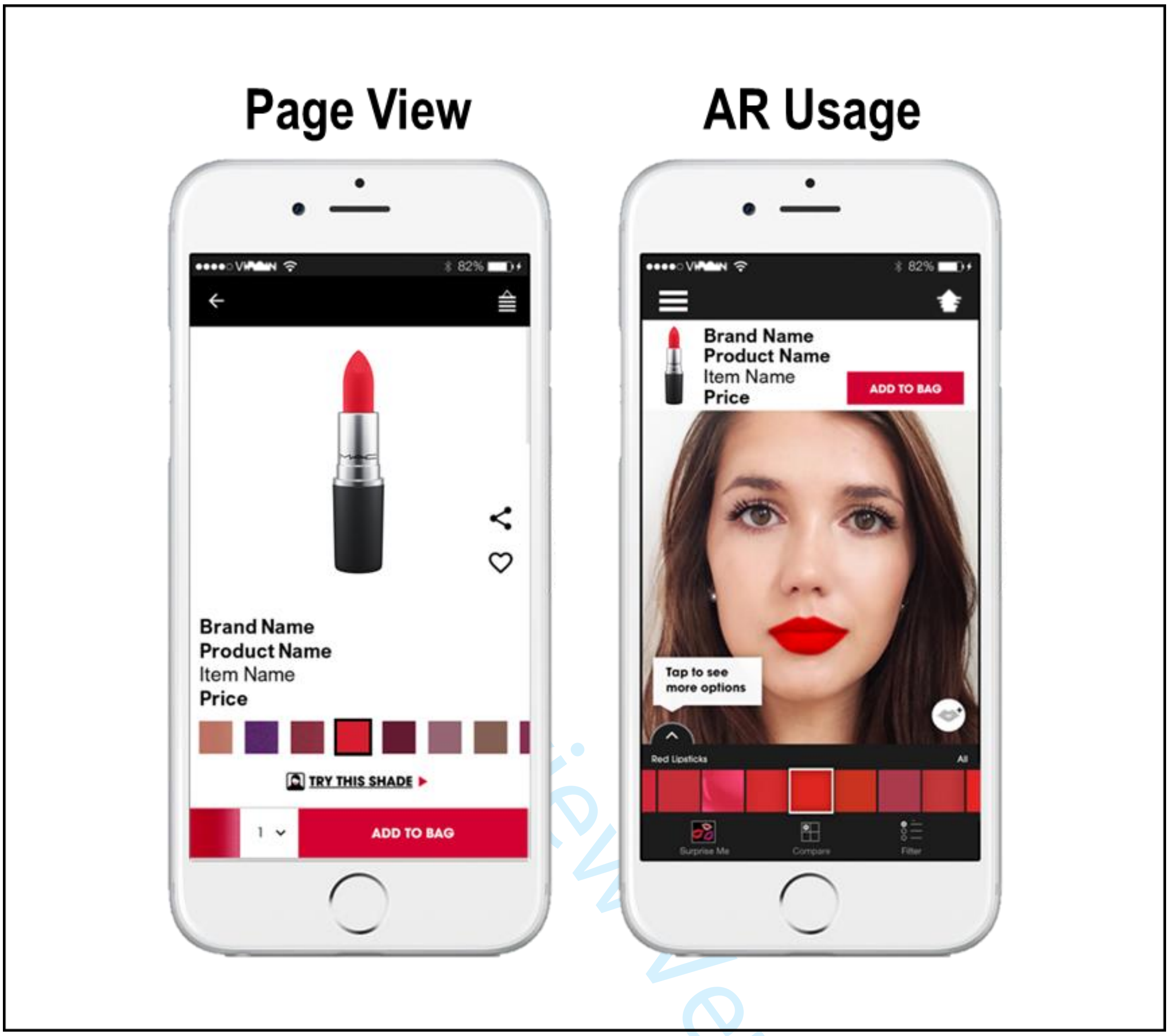
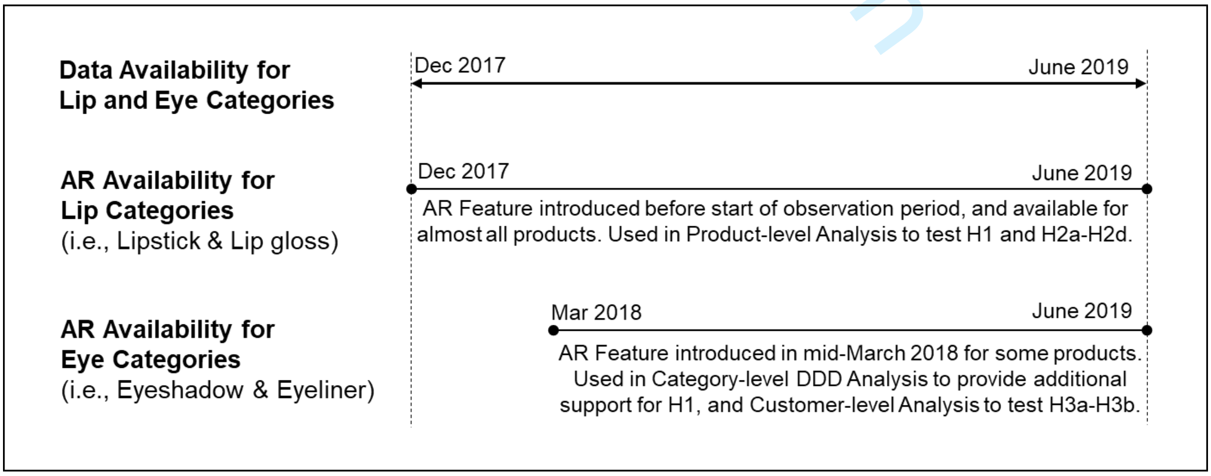


Figure A4. Overview of Data and AR Availability



WEB APPENDIX B: URL LINKS TO AR EXAMPLES

Brand	**URL Link**
Amazon	https://www.amazon.com/adlp/arview
Audi	https://www.audi-mediacenter.com/en/audimediatv/video/augmented-reality-2230
BMW	https://www.press.bmwgroup.com/global/article/detail/T0268031EN/bmw-i-augmented-reality-visualiser-launches-on-google-play
Hyundai	https://www.hyundai.news/eu/stories/how-augmented-reality-silently-revolutionises-your-driving-experience/
Ikea	https://www.ikea.com/au/en/customer-service/mobile-apps/say-hej-to-ikea-place-pub1f8af050
L'Oréal	https://www.wsj.com/articles/loreal-expands-virtual-try-on-service-11576776586
Lego	https://www.lego.com/en-gb/themes/hidden-side/ar-games
Lowe's	https://www.lowesinnovationlabs.com/instorenavigation
McDonalds	https://www.adsoftheworld.com/media/digital/mcdonalds_trackmymaccas_ios_app
Sephora	https://www.sephora.sg/pages/virtual-artist
Starbucks	https://stories.starbucks.com/stories/2017/starbucks-first-in-store-augmented-reality-experience/
Topshop	http://retail-innovation.com/topshop-in-moscow-had-a-virtual-fitting-room-on-trial
Toyota	https://www.campaignlive.co.uk/article/toyota-creates-augmented-reality-experience-new-model/1562609
Uniqlo	http://retail-innovation.com/uniqlos-magic-mirror
Walgreen	https://www.retaildive.com/ex/mobilecommercedaily/walgreens-to-fuse-digital-and-physical-experiences-via-virtual-shopping-technology
Walmart	https://corporate.walmart.com/newsroom/2012/04/25/walmart-joins-forces-with-marvels-the-avengers-to-transform-stores-into-a-super-heros-playground

Note: Links accessed on January 21, 2021

WEB APPENDIX C: CORRELATIONS TABLE FOR PRODUCT MODEL

Table C. Correlations Table for Product Model

	1[a]	2	3	4	5	6	7	8	9	10[b]	11[b]
1. Product Sales[a]	1.00										
2. AR Usage	.26	1.00									
3. AR Usage[Alt]	.27	1.00	1.00								
4. Brand Popularity	.22	.28	.28	1.00							
5. Brand Popularity[Alt]	.22	.28	.28	.98	1.00						
6. Appeal	.71	.21	.21	.23	.23	1.00					
7. Appeal[Alt]	.71	.21	.21	.24	.24	1.00	1.00				
8. Rating	.05	.06	.06	.04	.05	.05	.05	1.00			
9. Price	-.03	-.08	-.08	-.33	-.31	-.04	-.04	.10	1.00		
10. AR Usage[Country A;b]	.14	.75	.63	.17	.15	.09	.10	.03	-.06	1.00	
11. AR Usage[Country B;b]	.14	.64	.75	.15	.16	.10	.09	.03	-.04	.55	1.00

Notes: [a] Dependent variable
[b] Instruments; do not enter the second stage estimation equation

WEB APPENDIX D: INSTRUMENTAL VARIABLE ESTIMATION FOR PRODUCT MODEL

In the table below, we provide estimation results from the first stage model excluding instruments in Column (1), the first stage model including the two instruments AR $Usage^{Country\ A}$ and AR $Usage^{Country\ B}$ in Column (2), and the model without endogeneity correction in Column (3).

Table D. Additional Results from Instrumental Variable Estimation for Product Model

	Column (1) First Stage Model (Excluding Instruments)			Column (2) First Stage Model (With Instruments)			Column (3) Uncorrected Model		
AR Usage	-			-			-.004	(.006)	
Brand Popularity	4.655	(.130)	***	2.916	(.112)	***	1.192	(1.36)	
Appeal	.189	(.007)	***	.158	(.006)	***	.444	(.036)	***
Rating	.120	(.011)	***	.109	(.009)	***	.076	(.068)	
Price	-.001	(.001)		.001	(.001)	**	-.009	(.013)	
AR Usage × Brand Popularity	-			-			-.008	(.055)	
AR Usage × Appeal	-			-			-.000	(.001)	
AR Usage × Rating	-			-			.002	(.002)	
AR Usage × Price	-			-			.000	(.001)	
AR $Usage^{Country\ A}$	-			.414	(.010)	***	-		
AR $Usage^{Country\ B}$	-			.301	(.005)	***	-		
Constant	.956	(.062)	***	1.097	(.053)	***	-1.052	(.253)	***
Category dummies	Included			Included			Included		
Month dummies	Included			Included			Included		
Observations	29,345			29,345			29,345		
Log Likelihood	-100,245			-95,952			-18,634		

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

Note: Standard errors (clustered at product level) in parentheses

WEB APPENDIX E: ROBUSTNESS ANALYSES FOR PRODUCT MODEL

Table E. Results from Robustness Analyses for Product Model

	Column (1) Alternative Operationalization of AR Usage			Column (2) Alternative Operationalization of Brand Popularity and Appeal		
AR Usage	-.002	(.006)		.000	(.006)	
Brand Popularity	1.460	(.364)	***	2.639	(.554)	***
Appeal	.418	(.023)	***	.423	(.024)	***
Rating	.054	(.053)		.044	(.053)	
Price	-.009	(.004)	**	-.008	(.004)	**
H2a: AR Usage × Brand Popularity	**-. 020**	**(008)**	**	**-.048**	**(012)**	***
H2b: AR Usage × Appeal	**-.001**	**(.000)**	***	**-.001**	**(.000)**	***
H2c: AR Usage × Rating	**.001**	**(.001)**		**.001**	**(.001)**	
H2d: AR Usage × Price	**.000**	**(.000)**	**	**000**	**(.000)**	
Correction Term	.055	(.027)	**	.051	(.025)	**
Constant	-.917	(.253)	***	-0.947	(.260)	***
Category dummies	Included			Included		
Month dummies	Included			Included		
Observations	29,345			29,345		
Log Likelihood	-18,501			-18,501		

* *p ≤ .10; ** p ≤ .05; *** p ≤ .01*

Note: Standard errors (clustered at product level) in parentheses

WEB APPENDIX F: FALSIFICATION TESTS FOR CATEGORY DDD ANALYSIS

The DDD analysis relies on the assumption that the treatment and comparison groups follow the same trends in the absence of any intervention. Hence, any difference in trends in the post-treatment period can be attributed to the intervention. To test this assumption in our study, we conducted two falsification tests using data from the pre-AR introduction period.

Firstly, following Janakiraman, Lim, and Rishika (2018), we split the pre-AR introduction period into two halves. We then estimate Equation (2) following the same specification in the paper, but with one main difference: we replaced AR Intro_t with a new dummy variable, Test_t, which takes a value of 0 if the data belongs to the first half of the pre-AR introduction period, and 1 if the data belongs to the second half.

$$\text{(W1)} \quad \mathbf{X\beta_{jkt}} = \beta_0 + \beta_1 \text{Test}_t + \beta_2 \text{App}_k + \beta_3 \text{AR Feature}_j + \beta_4 \text{Test}_t \times \text{App}_k \times \text{AR Feature}_j$$

$$+ \beta_5 \text{Test}_t \times \text{App}_k + \beta_6 \text{Test}_t \times \text{AR Feature}_j + \beta_7 \text{App}_k \times \text{AR Feature}_j$$

$$+ \sum \gamma_c \text{Category}_j + \sum \delta_w \text{Week}_t + \varepsilon_{jkt}$$

Since the cut-off for the first and second half is arbitrary and there is no real intervention between these two periods, a non-significant three-way interaction between $\text{Test}_t \times \text{App}_k \times \text{AR Feature}_j$ would provide some support that the trend in app sales of eyeshadows and eyeliners vs the trends in sales for other channels/categories were similar prior to AR introduction. Conversely, a significant three-way interaction would indicate that the trends were already diverging before AR was introduced. As shown in the table below, the three-way interaction is not significant, providing support for the parallel trends assumption.

Table F1. Results for Falsification Test 1

	Falsification Test 1		
Test	1.057	(.297)	***
App	.052	(.138)	
AR Feature	.113	(.081)	
Test × App × AR Feature	**.227**	**(.269)**	
Test × App	.156	(.261)	
Test × AR Feature	-.097	(.207)	
App × AR Feature	-.161	(.142)	
Constant	2.577	(.189)	***
Category dummies	Included		
Week dummies	Included		
Observations	420		
Log Likelihood	-1,798		

* *p ≤ .10; ** p ≤ .05; *** p ≤ .01*

Note: Standard errors (clustered at category-channel level) in parentheses

Secondly, following Fisher, Gallino, and Xu (2019), we replace AR $Intro_t$ in Equation (2) with the trend, $Week_t$, giving us the following equation:

$$\text{(W2)} \quad \mathbf{X\beta_{jkt}} = \beta_0 + \beta_1 \text{Week}_t + \beta_2 \text{App}_k + \beta_3 \text{AR Feature}_j + \beta_4 \text{Week}_t \times \text{App}_k \times \text{AR Feature}_j$$

$$+ \beta_5 \text{Week}_t \times \text{App}_k + \beta_6 \text{Week}_t \times \text{AR Feature}_j + \beta_7 \text{App}_k \times \text{AR Feature}_j$$

$$+ \sum \gamma_c \text{Category}_j + \sum \delta_w \text{Week}_t + \varepsilon_{jkt}$$

Similarly, a non-significant three-way interaction between $Week_t \times App_k \times AR\ Feature_j$ would provide some support for the validity of the parallel trends assumption. As shown in the table below, the three-way interaction is not significant, suggesting that category sales were following similar trends prior to the introduction of AR.

Table F2. Results for Falsification Test 2

	Falsification Test 2		
Week	.003	(.001)	***
App	-24.375	(20.9)	
AR Feature	1.909	(15.4)	
Week × App × AR Feature	**.001**	**(.001)**	
Week × App	.001	(.001)	
Week × AR Feature	.000	(.001)	
App × AR Feature	-18.058	(21.7)	
Constant	-51.606	(18.9)	***
Category dummies	Included		
Week dummies	Included		
Observations	420		
Log Likelihood	-1,794		

** $p \leq .10$; ** $p \leq .05$; *** $p \leq .01$*
Note: Standard errors (clustered at category-channel level) in parentheses

We note that in both falsification tests, the coefficients for $Test_t$ and $Week_t$ are significant, indicating a general increasing sales trend in the pre-AR introduction period. However, the variables App_k and AR $Feature_j$, and their interactions with both $Test_t$ and $Week_t$ are not significant, indicating that the treatment and comparison groups are similar in both absolute values and channel / category-specific trends.

WEB APPENDIX G: ROBUSTNESS CHECKS FOR CATEGORY DDD ANALYSIS

We performed two additional robustness checks for the category DDD analysis. Firstly, we estimate the same model using a Poisson regression. Secondly, we split AR $Feature_j$, the dummy variable representing categories with the AR feature, into its two components, $Eyeshadow_j$ and $Eyeliner_j$. Results for both models are presented in the table below, and are consistent with the main model. To test if coefficients for the 3-way interaction for eyeshadow and eyeliner are significantly different, we used the Wald test for equality of coefficients. The result fails to reject the null hypothesis that the coefficients are the same (p = .756), indicating that the effect of AR introduction on sales is not product-specific.

Table G1. Robustness Checks for Category-level DDD Analysis

	Column (1) Poisson Model			**Column (2) Decomposing AR Feature into Constituent Categories**		
AR Intro	1.197	(.462)	***	.768	(.442)	*
App	51.500	(13.9)	***	39.142	(9.14)	***
AR Feature	13.123	(9.98)		-		
Eyeshadow	-			13.371	(6.75)	**
Eyeliner	-			1.238	(11.2)	
AR Intro × App × AR Feature	**.543**	**(.286)**	*****	-		
AR Intro × App × Eyeshadow	-			**.460**	**(.238)**	*
AR Intro × App × Eyeliner	-			**.408**	**(.238)**	*
AR Intro × App	.324	(.188)	*	.243	(.136)	*
AR Intro × AR Feature	-.144	(.261)		-		
AR Intro × Eyeshadow	-			.152	(.159)	
AR Intro × Eyeliner	-			-.281	(.250)	
App × AR Feature	-.069	(.084)		-		
App × Eyeshadow	-			-.014	(.036)	
App × Eyeliner	-			-.039	(.036)	
Constant	2.030	(.284)	***	2.403	(.224)	***
Category dummies	Included			Included		
Week dummies	Included			Included		
Category trend	Included			Included		
Channel trend	Included			Included		
Observations	1,080			1,080		
Log Likelihood	-14,331			-5,091		

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

Note: Standard errors (clustered at category-channel level) in parentheses

We also report results for the conventional differences-in-difference (DiD) analysis below. Column (1) presents results for the DiD at the channel-level. Thus, we only include observations for eye categories that have the AR feature (i.e., eyeshadow and eyeliner), and compare the differences in app vs web sales for these categories before and after the feature was introduced. Column (2) presents results for the DiD at the category-level. Thus, we only include observations for the app channel, and compare the differences in sales for categories with vs without the AR feature before and after the feature was introduced.

Across both models, the focal interactions are positive, similar in magnitude, and highly significant, indicating that differences in sales before and after the AR feature was introduced is higher in the treatment group (i.e., App for Channel-level model, and categories with AR feature in the Category-level model) compared to the respective control group.

Table G2. Results for the Conventional Differences-in-differences (DiD) Analysis at the Channel and Category Level

	Column (1) Channel-level (among eye categories with AR feature)			**Column (2) Category-level (within app channel)**		
AR Intro	.379	(.286)		-.310	(.279)	
App	23.206	(4.40)	***	-		
AR Feature	-			-.211	(.060)	***
AR Intro × App	**.342**	**(.112)**	***	-		
AR Intro × AR Feature	-			**.367**	**(.061)**	***
Constant	2.525	(.202)	***	2.595	(.195)	***
Category dummies	Included			Included		
Week dummies	Included			Included		
Category trend	Included			-		
Channel trend	Included			-		
Observations	432			540		
Log Likelihood	-1,950			-2,388		

** p ≤ .10; ** p ≤ .05; *** p ≤ .01*

Notes: Standard errors in parentheses. In Column (2), we omitted the Category trend because the model failed to converge when category trend is included. This could be due to the large number of parameters (more than a hundred) and smaller sample size (compared to the main DDD model). We also omitted Channel trend because there is only one channel (i.e., app).

WEB APPENDIX H: CORRELATIONS TABLE FOR CUSTOMER MODEL

Table H. Correlations Table for Customer Model

	1	2	3	4	5	6	7	8	9
1. Past Duration	1.00								
2. Past Pages^{Eyes}	.47	1.00							
3. Duration	.23	.09	1.00						
4. Pages^{Eyes}	.08	.09	.33	1.00					
5. Past Order Number	.14	.08	.17	.07	1.00				
6. Past Order Value	-.01	-.01	.03	.00	.07	1.00			
7. Past Eye Purchases	.02	.07	.03	.09	.45	.20	1.00		
8. Recent Order	-.13	-.07	-.09	-.04	-.42	-.01	-.19	1.00	
9. First Order	-.01	.01	.04	.02	.36	.09	.21	-.07	1.00

WEB APPENDIX I: IDENTIFICATION FOR CUSTOMER MODEL

We applied various identification strategies to address possible endogeneity issues in the customer model. The results from these analyses are presented in the tables below, and are qualitatively consistent with our findings from the uncorrected model in the main paper.

Tables I1, I2, and I3 are the results using a 12-month, 6-month, and 3-month period, respectively. For all tables, column (1) reports the first stage estimation (i.e., likelihood of customers using AR to try eye product in the focal period, AR $\text{Usage}_i^{\text{Eyes}}$). The instrument, Past AR $\text{Usage}^{\text{Lips}}$, is highly significant for all the time periods.

Column (2) and (3) report results from the 2-stage residual inclusion and Heckman selection methods respectively. In the 2-stage residual inclusion method, Correction Term refers to the residuals from the first stage estimation. In the Heckman selection model, Correction Term refers to the inverse Mills ratio. Across all models, the correction terms are not significant. Since the coefficient for the residual correction term in the 2-stage residual inclusion method is equivalent to the Hausman test for the presence of endogeneity (Papies, Ebbes, and Van Heerde 2017), the results suggest that endogeneity may not be a concern in the present context.

Column (4) reports results for the propensity score weighting approach. We use the first stage equation to calculate customers' propensity of using AR in the focal period, and include this as weights in the estimation of Equation (3). Following Bell, Gallino, and Moreno (2018), we calculate the weights as

$$\omega(\text{AR Usage}^{\text{Eyes}}, \text{x}) = \frac{\text{AR Usage}^{\text{Eyes}}}{\hat{\text{e}}(\text{x})} + \frac{1 - \text{AR Usage}^{\text{Eyes}}}{1 - \hat{\text{e}}(\text{x})'}$$

where $\hat{\text{e}}(\text{x})$ is the estimated probability of using AR in the focal period. While propensity score methods only account for observable factors that affect AR usage, the estimation results are qualitatively consistent with the main model, providing additional confidence in the findings.

Table I1. Results from Various Identification Methods for 12-Month Customer Model

	Column (1) First Stage Model	**Column (2) Second Stage (2 Stage Residual Inclusion)**	**Column (3) Second Stage (Heckman Selection)**	**Column (4) Second Stage (Propensity Score Weighting)**
AR Usage^{Eyes}	-	-.529 (.501)	.076 (.068)	-.030 (.015) **
New Channel	.041 (.017) **	-.340 (.020) ***	-.343 (.019) ***	-.354 (.017) ***
New Category	-.024 (.020)	-.136 (.021) ***	-.134 (.021) ***	-.156 (.018) ***
H3a: AR Usage^{Eyes} × New Channel	-	**.092 (.046) ****	**.089 (.046) ***	**.088 (.024) *****
H3b: AR Usage^{Eyes} × New Category	-	**.080 (.045) ***	**.085 (.045) ***	**.083 (.023) *****
Past Duration	-.001 (.000) *	-.002 (.000) ***	-.002 (.000) ***	-.002 (.000) ***
Past Pages^{Eyes}	-.000 (.003)	-.003 (.003)	-.003 (.003)	-.003 (.002)
Duration	.001 (.000) ***	.000 (.000) ***	.000 (.000) ***	.000 (.000) ***
Pages^{Eyes}	.009 (.000) ***	.009 (.001) ***	.008 (.000) ***	.008 (.000) ***
Past Order Number	-.012 (.002) ***	.006 (.002) ***	.007 (.002) ***	.002 (.001) *
Past Order Value	-.000 (.000) **	.002 (.000) ***	.002 (.000) ***	.002 (.000) ***
Past Eye Purchases	.017 (.006) ***	.082 (.006) ***	.081 (.006) ***	.074 (.004) ***
Recent Order	-.003 (.003)	-.020 (.004) ***	-.020 (.004) ***	-.020 (.003) ***
First Order	-.001 (.001)	-.001 (.001)	-.001 (.001)	-.000 (.001)
Instrument: Past AR Usage^{Lips}	.176 (.049) ***	-	-	-
Correction Term	-	.204 (.199)	-.077 (.051)	-
Constant	-1.325 (.035) ***	-1.190 (.091) ***	-1.259 (.037) ***	-1.247 (.026) ***
Observations	42,493	42,493	42,493	42,493
Log Likelihood	-16,239	-16,609	-16,609	-31,603

* *p ≤ .10; ** p ≤ .05; *** p ≤ .01;* Note: Standard errors in parentheses

Table I2. Results from Various Identification Methods for 6-Month Customer Model

	Column (1) First Stage Model (With Instruments)			Column (2) Second Stage (2 Stage Residual Inclusion)			Column (3) Second Stage (Heckman Selection)			Column (4) Second Stage (Propensity Score Weighting)		
AR Usage^{Eyes}	-			-.886	(.565)		.001	(.103)		.002	(.022)	
New Channel	.022	(.024)		-.320	(.029)	***	-.323	(.029)	***	-.319	(.026)	***
New Category	-.029	(.029)		-.065	(.032)	**	-.060	(.032)	*	-.097	(.027)	***
H3a: AR Usage^{Eyes} × New Channel	**-**			**.150**	**(.070)**	******	**.144**	**(.070)**	******	**.139**	**(.035)**	*******
H3b: AR Usage^{Eyes} × New Category	**-**			**.076**	**(.068)**		**.075**	**(.068)**		**.057**	**(.033)**	*****
Past Duration	-.002	(.000)	***	-.002	(.000)	***	-.002	(.000)	***	-.002	(.000)	***
Past Pages^{Eyes}	-.001	(.002)		-.000	(.002)		.000	(.002)		.004	(.002)	**
Duration	.001	(.000)	***	.001	(.000)	***	.001	(.000)	***	.001	(.000)	***
Pages^{Eyes}	.010	(.000)	***	.010	(.001)	***	.008	(.000)	***	.008	(.000)	***
Past Order Number	-.018	(.003)	***	.002	(.004)		.005	(.003)		.002	(.002)	
Past Order Value	-.001	(.000)	***	.002	(.000)	***	.002	(.000)	***	.002	(.000)	***
Past Eye Purchases	.014	(.012)		.106	(.012)	***	.103	(.012)	***	.083	(.008)	***
Recent Order	-.006	(.005)		-.021	(.006)	***	-.020	(.006)	***	-.013	(.004)	***
First Order	-.002	(.002)		-.002	(.002)		-.002	(.002)		-.001	(.001)	
Instrument: Past AR Usage^{Lips}	.301	(.051)	***	-			-			-		
Correction Term	-			.350	(.221)		.002	(.072)		-		
Constant	-1.285	(.051)	***	-1.408	(.114)	***	-1.567	(.057)	***	-1.579	(.040)	***
Observations	24,147			24,147			24,147			24,147		
Log Likelihood	-8,239			-7,422			-7,423			-14,568		

* *$p \leq .10$; ** $p \leq .05$; *** $p \leq .01$;* Note: Standard errors in parentheses

Table I3. Results from Various Identification Methods for 3-Month Customer Model

	Column (1) First Stage Model (With Instruments)			Column (2) Second Stage (2 Stage Residual Inclusion)			Column (3) Second Stage (Heckman Selection)			Column (4) Second Stage (Propensity Score Weighting)		
AR Usage^{Eyes}	-			-.394	(.539)		.182	(.240)		-.038	(.030)	
New Channel	.007	(.040)		-.295	(.040)	***	-.295	(.040)	***	-.280	(.038)	***
New Category	-.042	(.045)		-.124	(.042)	***	-.123	(.042)	***	-.128	(.038)	***
H3a: AR Usage^{Eyes} × New Channel	**-**			**.092**	**(.138)**		**.083**	**(.139)**		**.042**	**(.053)**	
H3b: AR Usage^{Eyes} × New Category	**-**			**-.004**	**(.134)**		**-.003**	**(.135)**		**-.049**	**(.049)**	
Past Duration	-.002	(.000)	***	-.002	(.000)	***	-.002	(.000)	***	-.001	(.000)	***
Past Pages^{Eyes}	-.001	(.002)		-.004	(.002)	**	-.004	(.002)	**	-.002	(.001)	
Duration	.001	(.000)	***	.001	(.000)	***	.001	(.000)	***	.001	(.000)	***
Pages^{Eyes}	.019	(.001)	***	.018	(.002)	***	.017	(.001)	***	.018	(.001)	***
Past Order Number	-.021	(.005)	***	.002	(.005)		.002	(.004)		.004	(.003)	
Past Order Value	-.001	(.000)	***	.002	(.000)	***	.002	(.000)	***	.002	(.000)	***
Past Eye Purchases	.029	(.014)	**	.064	(.011)	***	.063	(.011)	***	.062	(.008)	***
Recent Order	-.001	(.008)		-.016	(.008)	*	-.016	(.008)	**	.013	(.006)	**
First Order	-.004	(.003)		.004	(.003)	*	.005	(.002)	*	.005	(.002)	***
Instrument: Past AR Usage^{Lips}	.601	(.061)	***	-			-			-		
Correction Term	-			.137	(.203)		-.134	(.139)		-		
Constant	-1.551	(.081)	***	-1.722	(.106)	***	-1.752	(.079)	***	-1.885	(.058)	***
Observations	13,434			13,434			13,434			13,434		
Log Likelihood	-2,903			-3,773			-3,772			-7,107		

* *p ≤ .10;* ** *p ≤ .05;* *** *p ≤ .01;* Note: Standard errors in parentheses

WEB APPENDIX J: ROBUSTNESS ANALYSES FOR CUSTOMER MODEL

Table J. Results from Robustness Analyses for 12-Month Customer Model

	Column (1) Dependent Variable as Number of Eye Products Purchased in Focal Period	**Column (2) AR Usage^{Eyes} as Number of AR Sessions**	**Column (3) Alternative Operationalization of Channel and Category Experience**
AR Usage^{Eyes}	-.042 (.052)	-.011 (.021)	.075 (.019) ***
New Channel	-.636 (.035) ***	-.342 (.019) ***	-
New Category	-.277 (.038) ***	-.131 (.021) ***	-
Channel Exp	-	-	.076 (.003) ***
Category Exp	-	-	.103 (.006) ***
H3a: AR Usage^{Eyes} × New Channel	**.177 (.083) ****	**.062 (.031) ****	-
H3b: AR Usage^{Eyes} × New Category	**.185 (.081) ****	**.052 (.031) ***	-
H3a: AR Usage^{Eyes} × Channel Exp	-	-	**-.012 (.005) ****
H3b: AR Usage^{Eyes} × Category Exp	-	-	**-.018 (.009) ****
Past Duration	-.004 (.001) ***	-.002 (.000) ***	-.002 (.000) ***
Past Pages^{Eyes}	-.002 (.005)	-.003 (.003)	-.003 (.003)
Duration	.000 (.000) ***	.000 (.000) ***	.000 (.000) ***
Pages^{Eyes}	.013 (.001) ***	.007 (.000) ***	.008 (.000) ***
Past Order Number	.017 (.003) ***	.007 (.002) ***	-.013 (.002) ***
Past Order Value	.004 (.000) ***	.002 (.000) ***	.002 (.000) ***
Past Eye Purchases	.145 (.009) ***	.080 (.006) ***	-
Recent Order	-.041 (.007) ***	-.020 (.004) ***	-.030 (.004) ***
First Order	-.005 (.002) **	-.001 (.001)	.006 (.001) ***
Constant	-1.931 (.063) ***	-1.277 (.035) ***	-1.606 (.029) ***
Observations	42,493	42,493	42,493
Log Likelihood	-23,262	-16,610	-16,502

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

Notes: Standard errors in parentheses. In column (3), Channel Exp and Category Exp have an inverse relationship with New Channel and New Category, respectively. Category Exp is operationalized as the number of eye products purchased in the pre-AR Introduction period, so it is equivalent to Past Eye Purchases.

WEB APPENDIX K: IMPACT OF AR USAGE ON WEB AND OFFLINE SALES

Table K1. Impact of AR Usage on Web Sales

	Column (1) 12-Month Model			Column (2) 6-Month Model			Column (3) 3-Month Model		
AR Usage^{Eyes}	.011	(.033)		-.065	(.067)		-.053	(.132)	
New Channel	-.341	(.022)	***	-.294	(.042)	***	-.330	(.068)	***
New Category	-.186	(.024)	***	-.130	(.045)	***	-.079	(.066)	
AR Usage^{Eyes} × New Channel	**-.012**	**(.054)**		**.045**	**(.113)**		**.256**	**(.226)**	
AR Usage^{Eyes} × New Category	**.106**	**(.052)**	**	**.021**	**(.108)**		**-.103**	**(.232)**	
Past Duration	-.003	(.000)	***	-.002	(.001)	***	-.001	(.001)	*
Past Pages^{Eyes}	.002	(.003)		.005	(.003)		-.004	(.004)	
Duration	.000	(.000)	***	.000	(.000)		.000	(.000)	
Pages^{Eyes}	.004	(.000)	***	.004	(.001)	***	.009	(.002)	***
Past Order Number	.014	(.002)	***	.009	(.004)	*	.016	(.007)	**
Past Order Value	.002	(.000)	***	.003	(.000)	***	.003	(.001)	***
Past Eye Purchases	.050	(.006)	***	.051	(.016)	***	.019	(.017)	
Recent Order	-.011	(.004)	***	-.021	(.008)	**	-.013	(.014)	
First Order	.004	(.001)	**	.003	(.003)		.008	(.004)	*
Constant	-1.635	(.041)	***	-2.113	(.079)	***	-2.438	(.126)	***
Observations	42,493			24,147			13,434		
Log Likelihood	-12,414			-3,308			-1,355		

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

Note: Standard errors in parentheses

Table K2. Impact of AR Usage on Offline Sales

	Column (1) 12-Month Model			Column (2) 6-Month Model			Column (3) 3-Month Model		
AR Usage^{Eyes}	.088	(.027)	***	.098	(.041)	**	-.084	(.078)	
New Channel	.302	(.015)	***	.283	(.022)	***	.244	(.031)	***
New Category	-.196	(.017)	***	-.161	(.026)	***	-.143	(.035)	***
AR Usage^{Eyes} × New Channel	**.009**	**(.039)**		**.008**	**(.058)**		**.273**	**(.113)**	**
AR Usage^{Eyes} × New Category	**.010**	**(.039)**		**.001**	**(.059)**		**.014**	**(.117)**	
Past Duration	-.003	(.000)	***	-.002	(.000)	***	-.002	(.000)	***
Past Pages^{Eyes}	.002	(.003)		.001	(.002)		-.001	(.002)	
Duration	.000	(.000)		.000	(.000)		.000	(.000)	
Pages^{Eyes}	.004	(.000)	***	.003	(.000)	***	.007	(.001)	***
Past Order Number	.027	(.001)	***	.026	(.003)	***	.019	(.004)	***
Past Order Value	.001	(.000)	***	.002	(.000)	***	.002	(.000)	***
Past Eye Purchases	.135	(.006)	***	.140	(.010)	***	.108	(.010)	***
Recent Order	-.042	(.003)	***	-.037	(.005)	***	-.040	(.007)	***
First Order	.013	(.001)	***	.009	(.001)	***	.007	(.002)	***
Constant	-1.026	(.030)	***	-1.390	(.046)	***	-1.481	(.064)	***
Observations	42,493			24,147			13,434		
Log Likelihood	-25,043			-11,830			-5,686		

* *p ≤ .10;* ** *p ≤ .05;* *** *p ≤ .01*

Note: Standard errors in parentheses

WEB APPENDIX L: SURVEY WITH MARKETING PRACTITIONERS

To determine the practical importance of the five research themes, we conducted an online survey with marketing practitioners from companies that are either currently using, or planning to use, AR for marketing, advertising, or retailing activities. We used a multi-pronged approach to recruit respondents, including reaching out to our personal network of industry contacts and identifying suitable respondents on LinkedIn. In total, we managed to collect 36 responses across a 3-week period. The background of survey respondents is provided in Table L.

Table L. Background of Survey Respondents (n=36)

Variable	Level	%
Geographical Region (based on IP address location)	Asia	38.9
	United States	30.6
	Europe	22.2
	Australasia	5.6
	South America	2.8
Job Function	Digital Marketing	55.6
	Senior Management (CEO/CMO)	16.7
	Advertising	8.3
	Sales / Business Development	8.3
	Retailing	5.6
	Marketing (Generalist)	2.8
	Customer Relationship Management	2.8
Company Size	Large (more than 500 employees)	33.3
	Medium (100-500 employees)	27.8
	Small (less than 100 employees)	38.9
AR usage for marketing, advertising, or retailing activities	Company is currently using AR	75.0
	Company is not using AR, but planning to use it in the next 3 years	25.0

We presented each research theme (and the associated topics) separately to respondents, and asked them to rate it in terms of importance on a 7-point scale (1 = Not important at all, 7 = Extremely important). The order of research themes were randomized across respondents to avoid primacy and recency effects. After the five research themes were rated independently, we presented all the research themes on the same screen and asked respondents to rank them in terms of importance using a drag-and-drop function (1st position from top = Most important, 5th position from top = Least important). Similarly, the order of research themes from top to bottom of the screen were randomized across respondents.