Engaging the unengaged customer: The value of a retailer mobile app

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Engaging the unengaged customer: The value of a retailer mobile app

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A B S T R A C T

Mobile apps are becoming a go-to tactic for retailers because they offer the promise of highly convenient digital engagement. We hypothesize that two types of customers are best served by these apps — "offline-only" customers currently purchasing exclusively from the retailer's physical store, and "distant" customers who reside far from the physical store. For offline-only customers, the app complements the physical engagement they currently have. For distant customers, the app offers convenient engagement their remoteness currently precludes. We model app access and purchase behavior of 629 customers who downloaded a retailer's app. We find that apps generate more incremental sales among distant customers compared to near customers, and more incremental sales among offline-only customers compared to online customers. On an illustrative base of 100 K app users, we find accessing the app would generate $2.3 M in incremental sales. Consistent with our segmentation results, we find that the users with the greatest purchase lift (9.5%) due to app usage are those that are distant and offline-only. Our results confirm the economic value of retailer apps and their role as a segmentation strategy to enhance customer engagement.

1. Introduction

In today's intensely competitive marketplace, retailers have turned to mobile apps as a means to increase customer value. A primary motivation for offering retailer apps is their potential to enhance customer engagement (Gill, Sridhar, & Grewal, 2017; Inman & Nikolova, 2017). Engagement entails non-transactional interactions with the retailer such as physically assessing the fit and feel of products, drawing on the expertise of a salesperson or of user reviews, and identifying alternative products using the retailer's online recommendations (van Doorn et al., 2010, p. 253). Apps foster engagement by providing a richer, deeper shopping experience than standard websites (Bellman, Potter, Treleaven-Hassard, Robinson, & Varan, 2011; Kim, Lin, & Sung, 2013; Liu, Lobschart, Verhoef, & Zhao, 2018; Wang, Krishnamurthi, & Malthouse, 2018). Among consumers, they are also very popular, as a recent survey by Synchrony found two-thirds of consumers have downloaded a retailer app (Synchrony, 2018). In the same study, a senior marketing executive asserts, "In today's competitive landscape, a mobile application is not just another piece of technology for retailers, it is a vital tool to engage shoppers with their brand" (Synchrony, 2018). Evidence suggests that engaging customers is important because it increases customer value (Gill et al., 2017; Kumar & Pansari, 2016).

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Kannan and Li (2017) note, "with use of mobile apps becoming popular, the impact of apps on customer usage of the mobile channels, spending and customer loyalty are emerging as important areas of inquiry." A natural question in assessing this impact is which customer segments are best served by the app. By focusing only on customers who access the app we can provide a more detailed investigation of the heterogeneity within this ever-growing user group. We propose two key segmentation variables: distance from the physical store and current channel usage. Our proposition is that the retailer app best serves current offline-only customers and distant customers. Offline-only customers (those who never bought online) may be "physically" engaged with the retailer, but may not be "digitally" engaged with the retailer.[1] The offline-only customer can physically examine the product and talk in-person with sales personnel. However, physical engagement lacks access to online reviews, online recommendations, and easy comparison of alternative products; that is, digital engagement. The app offers offline-only customers convenient access to digital engagement, thus increasing their total engagement and customer value. It provides an entirely new communications/purchase channel to the offline-only customer.

Distant customers, because of their remoteness to the physical store, face a barrier to engaging with the retailer because they lack the convenience to physically interact with the retailer. An app provides convenient digital engagement superior to what they might obtain now if they visit the retailer's website through their mobile or desktop device.

The objective of this paper is to empirically test the proposition that retailer apps especially enhance the value of offline-only and distant customers. To accomplish this, we develop a framework of how customers access (i.e., use) the app and how access translates into purchase, identifying three mechanisms by which the app may enhance distant more than near customer value and offline-only more than online customer value: (1) less wear-out in app access (2) enhanced encouragement of future app access ("app state dependence"), and (3) a stronger translation of app access into purchase.

We examine these mechanisms by developing a two-equation model of app access and purchase. The model's coefficients are fully heterogeneous in unobserved heterogeneity. We investigate observed heterogeneity by using customer location and prior channel usage as moderators of wear-out, state dependence, and access-to-purchase translation. We apply the model to study the performance of a retailer app for customers who have downloaded the app. We utilize a unique database of 629 customers over a 77-week period that records when customers access the app and when they purchase.

We find that retailer apps enhance the value of distant customers more than near customers, and offline-only customers more than online customers. Stronger access-to-purchase translation applies to both customer segments. That is, a given access of the app more likely translates into purchase for distant and offline-only customers. The stronger translation of access to purchase for offline-only vs. online customers suggests that the app offers online customers *improved* digital engagement, whereas for offline-only customers, it offers *an entirely new way* to engage with the retailer. The access state dependence mechanism works for distant customers but not offline-only customers. The reduction in wear-out does not apply to either customer segment. Therefore, the main mechanism by which the app enhances customer value is through higher probability translation of app access into purchase.

The economic impact of our findings is substantial. Among an illustrative base of 100,000 app users, we find accessing the app generates incremental sales of $2.3 M. Consistent with our results, we find that the users with the greatest purchase lift (9.5%) due to app usage are those that are distant and only use the offline channel. The consequences of app usage are managerially important, and crystalize the role of retailer apps as a segmentation strategy.

Our paper contributes as follows: First, we develop a framework and use a benefits/costs rationale to propose why consumer segments defined by distance from the store and channel usage respond differentially to the app. Second, we show empirically, as proposed, that distant and offline-only customers benefit the most from the app.

We proceed with a review of the literature to develop a framework for how consumers access the app and how this translates into purchase. We then state propositions detailing for which customers the app should be more effective. Next we discuss the data, specify the model, and describe estimation. We then present results and conclude with a discussion of implications.

2. Literature

Our paper contributes to the multichannel and customer engagement literatures. We follow De Haan, Kannan, Verhoef, and Wiesel (2018) and consider the online channel to consist of both fixed (desktop or laptop) and mobile shopping. We view apps as a particular type of mobile online channel. Regarding engagement, the literature discussed below suggests the benefits of the app are to provide convenient access to superior digital engagement, while the app will also impose costs related to learning and habit-change. These benefits and costs are relevant for both customer location and current channel usage, as the review below shows. We start with the literature on engagement.

2.1. Customer engagement

van Doorn et al. (2010), p. 253) define customer engagement as "a behavioral manifestation toward the brand or firm that goes beyond transactions."[2] Several non-transactional manifestations of engagement have attracted attention. These include research shopping, where the customer gathers information on one channel before possibly purchasing on another (Verhoef, Neslin, &

[1] We thank an anonymous reviewer for originating this distinction and encouraging us to draw on it.

[2] Kumar et al. (2010, pp. 297–298) consider transactions to be part of engagement. Our ensuing discussion draws primarily on non-transactional factors rather than transactions per se.

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Vroomen, 2007), posting and reading product reviews (King, Racherla, & Bush, 2014; Reichelt, Sievert, & Jacob, 2014), interacting with sales personnel either in person or through online chat (Chang, Zhang, & Neslin, 2018), physically inspecting the product (Chang et al., 2018), and expressing opinions about the retailer through social media (Moe & Schweidel, 2014). Evidence suggests that engaging customers is important because it increases customer value (Gill et al., 2017; Kumar & Pansari, 2016).

It is useful to distinguish between "digital" and "physical" engagement. Digital engagement refers to non-transactional shopping activities available online, such as easy access to consumer reviews, online chat services, and alternative products suggested by website recommendations. Physical engagement refers to non-transactional shopping activities available offline, in the physical store. These include physical inspection of products, personal interaction with store personnel, and drawing on family and friends' opinions when shopping together. We draw on these concepts to identify what the literature says retailer apps provide to customers.

2.2. Retailer apps and customer engagement

Researchers have only recently investigated retailer apps and customer engagement. Kim et al. (2013) study the content of 106 "branded" apps, and conclude, "By providing consumers unique experiences associated with their brands, companies are able to use branded apps to engage with consumers more effectively." (p. 53). Later, Kim, Wang, and Malthouse (2015) use propensity score matching to compare adopters and non-adopters of retailer apps. They find that retailer apps increase sales "because they provide portable, convenient, and interactive engagement opportunities, allowing customers to interact with the brand on a habitual basis." (p. 28). Wang et al. (2018) find that the provision of a retailer app enhances the performance of a loyalty program. The authors attribute this to the "information convenience" (p. 316) provided by the app. Using a lab experiment, Bellman et al. (2011) determine that "The most likely explanation for the effectiveness of branded apps is that they offer a high level of user engagement, based on rich experiences that in this experiment were either information or experiential." (p. 198).

This suggests that convenience and superior digital engagement are what retailer apps offer customers. However, visiting the retailer's website directly also offers digital engagement and it is natural to consider what a retailer app offers that regular online shopping, i.e., directly visiting the retailer's website, does not. To our knowledge there has not been much academic research comparing the app channel and online shopping. De Haan et al. (2018) study mobile vs. "fixed" online shopping, not apps. They note that mobile's portability means it can be searched at any time and place, so convenience is important for mobile visits and presumably for retailer apps as well. Huang, Lu, and Ba (2016) note also the convenience of mobile apps as a reason customers may switch from the website to the mobile app (see Liu, Lobschat, & Verhoef, 2018 p. 3). Liu, Lobschart, et al. (2018) suggest that flexibility, convenience, customer experience and lower risk contribute to an increase in sales among mobile website users who adopt a retailer app.

The practitioner literature is rife with debate on the merits of a retailer's app vs. its website. The consensus appears to be that a website is a home base that comes first. But, apps bring the website to life. They serve customers seeking deeper, more convenient digital engagement. YML (2018), a mobile consultancy, points out the following ways in which apps achieve this: (1) Apps are particularly amenable to organization on one's mobile desktop in a prominent location. (2) Apps provide instant, one-click access to the retailer, rather than the two-step process of opening a mobile browser and typing in the name of the retailer. (3) Apps are effective at delivering push notifications, an important way to increase customer retention. (4) Apps are easier to personalize because they link directly to the mobile user's account.

While the literature does identify the benefits of retailer apps, it has less to say about the costs. De Haan et al. (2018) suggest that a mobile device's small screen makes it difficult for consumers to process the information they need to make a purchase. While the consumer can sometimes address this by using a mobile tablet rather than a mobile phone, many consumers will want to use their phone, and thus must learn how to process app information effectively on that device. This relates to what Konus, Verhoef, and Neslin (2008) call a "search" cost and Konus, Neslin, and Verhoef (2014) call an "adjustment" cost. We will use the moniker "learning" cost to summarize these costs. Konus et al. (2008) also describe a switching cost to channel choice. Switching to a new channel requires customers to shift from their current routine of shopping, that is, a change in shopping habit. We therefore identify two costs in using the retailer app — learning and habit change.

In summary, the literature suggests the "value proposition" delivered by retailer apps is more convenient access to superior digital engagement than that provided by visiting the retailer's website directly. We can also distill two costs in using the app – learning and habit change. These benefits and costs are particularly relevant to two customer characteristics: customer location and current channel usage.

2.3. The impact of apps and customer location: distant vs. near customers

Customer distance from the physical store has long been a subject of academic research (Huff, 1964). Bell and Lattin (1998) found that distance from the store influenced store choice, while Thang, Lin, and Tan (2003) found using survey data that "accessibility" was the second most important out of eight factors influencing store preference.

Recent literature suggests that the online channel has diminished the role of location (Ailawadi and Keller 2004; Kumar, Anand, & Song, 2017). However, the online channel is not a complete substitute for the physical store. Pozzi (2013) finds only 45% of the online sales generated by the addition of a retail website cannibalized (substituted for) offline sales, *and* cannibalization is lower for households living farther away from stores, "consistent with the idea that the online service is enhancing the appeal of the retailer to customers who would otherwise be unlikely to shop there because of the high travel costs" (p. 571).

Some studies have examined the impact of adding a *retail website* on distant vs. near customers. Shriver and Bollinger (2017) find that a 1% increase in a customer's distance from the physical store is associated with a 0.197% increase in online sales. Luo, Zhang, Dou, and Zeng (2016) find coupons targeted at distant online customers are most effective at increasing profits. These studies suggest that distant customers may benefit more than near customers. In contrast, Melis, Campo, Lamey, and Breugelmans (2016) find that the gains in sales from customers who buy online are largest among customers who live *closer* to the physical store. Additionally, Van Nierop, Leeflang, Teerling, and Huizingh (2011) study the impact of an informational website on physical product sales. They find that distant users of the website are *less* likely to purchase than near users. We conjecture this could be because the informational website, by not including purchase, did not provide the convenience apps offer in translating information provided by the app into purchase.

The most closely related research to ours that investigates distance and mobile app usage is Narang and Shankar (2017). They study the effect of *app adoption* on purchase and product returns, whereas we study the next step: once the app is adopted, how do consumers *access the app* and how does that translate into purchase? While Narang and Shankar (2017) use distance as a covariate in the app adoption and product return decisions, we are the first to study how distance affects app access and how it moderates the effect of app access on purchase behavior.

It is interesting to note that retailer apps might be viewed as a modern form of catalog in that they allow the distant customer to engage with the retailer remotely. However, drawing from the afore-noted attributes of apps, apps are more interactive, more uniquely personal, and more tied to up-to-the-minute offerings than could be communicated via catalog.

In summary, research on online shopping reaches mixed conclusions as to whether the benefits of online accrue more to distant or near customers. However, this pertains to online shopping, not retailer apps as a particular form of online shopping. To our knowledge, no study has examined a retailer app's impact on sales generated by distant vs. near users.

2.4. The impact of apps and customer channel usage: online vs. offline-only customers

Several studies find that adding the online channel to an already established offline channel increases total sales, and vice versa. Biyalogorsky and Naik (2003) find that adding the online channel increases total sales across all channels without completely cannibalizing the offline channel. Deleersnyder, Geyskens, Gielens, and Dekimpe (2002) echo these results, with the important proviso that the internet channel not imitate the offline channel too closely. Geyskens, Gielens, and Dekimpe (2002) find that the stock market reacted positively to the addition of the online channel. More recently and consistent with Pozzi (2013), Melis et al. (2016) conclude that total sales increase among consumers who decide to buy online from a retailer.

Regarding the impact of adding the offline channel to an established online channel, Pauwels and Neslin (2015) report that adding a physical store does not cannibalize online sales in the region where the store is located. Avery, Steenburgh, Deighton, and Caravella (2012) find similar results in the short run, but in the long run online and call center sales both benefit from the physical store.

The above literature investigates the profit impact of adding online or offline channels. The question is which current customers are more likely to benefit from a retailer app — online or offline-only customers? The literature noted earlier suggests that the comparison of a retailer app vs. accessing the website directly is one of degree. The app offers online users currently visiting the website a *superior* online experience, not a *totally different kind* of experience. However, for customers not currently utilizing the website as much – presumably, offline-only customers – the retailer app provides a new type of experience, a new channel.

This links to the ample research finding that the multichannel customer is a more valuable customer (Montaguti, Neslin, & Valentini, 2016; also see their literature review). Montaguti et al. (2016) show in a field experiment that average customer value increases when marketing is used to increase in the number of multichannel customers.

One might question whether the retail app offers enough superior digital engagement to benefit the offline-only customer who currently experiences physical engagement. Offline-only customers may simply belong to the large single-channel segment that prefers to shop and engage in the physical store exclusively. The existence of this segment has been identified by Konus et al. (2008) and De Keyser, Schepers, and Konus (2015).

2.5. Literature review summary

The literature review suggests that the “value proposition” of retailer apps is to deliver convenient access to a superior digital engagement than that provided by visiting the retailer's website directly. The benefits can be categorized into two groups: a) convenience, which is evidenced by studies focused on “informational convenience”, and “portability” and b) superior digital engagement, as evidenced by studies that identify “unique”, “interactive”, “less risk” and “rich experience” benefits (Bellman et al., 2011; De Haan et al., 2018; Kim et al., 2013; Kim et al., 2015; Liu, Lobschart, et al., 2018; Wang et al., 2018; YML, 2018). While the literature has less to say about the costs for the customer to use the retailer app, we were able to identify two: learning (De Haan et al., 2018; Konus et al., 2008; Konus et al., 2014) and habit change (Konus et al., 2008).

Convenience and digital engagement benefits, combined with learning and habit-change costs, evoke two customer characteristics: distance from the physical store (distant vs. near) and channel usage (offline-only vs. online). These are two key segmentation variables for retailers. Our contribution to the literature is to study how retailer apps differentially affect these segments. As noted earlier, previous research has not investigated the app channel vs. regular online shopping. By assessing the effectiveness of the app on online vs. offline-only customers, part of our contribution is to address this gap in the literature.

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3. Framework and propositions

Our research studies how customers behave after installing a retailer app. The framework in Fig. 1 traces the process by which users access an app and access translates into purchase. The framework proposes that distance and channel usage moderate this process at four points: (1) the impact of wear-out on access, (2) the impact of state dependence on access, (3) access frequency, and (4) the translation of app access into purchase.

Apps are notorious for a rapid drop in usage over time, as some users lose interest or find the app unhelpful (Chen, 2018; Kim et al., 2015; Localytics, 2018; Racherla, Furner, & Babb, 2012). If in fact customers find apps engaging, there should be positive feedback – state dependence – whereby current app access encourages future app access. While not consumer actions, and hence of less direct interest, retailer marketing such as advertising may also influence access. Hence we consider marketing as a control variable.

We draw on our framework and the literature review to develop propositions regarding for whom the retailer app will be more successful: distant versus near customers, and offline-only (solely offline purchasing) versus online customers (customers with at least some online purchasing). We utilize a cost/benefit approach to developing these propositions. This posits that customer decisions are based on what they *perceive* to be the benefits and costs of alternatives, and has been used in previous research regarding shopping and channel choices (Gijsbrechts, Campo, & Nisol, 2008; Konus et al., 2008; Konus et al., 2014). The literature review identified the benefits of the retailer app to be convenience and superior digital engagement. The costs are learning and habit change required to use the app. As articulated by our framework, wear out, state dependence, access frequency, and translation of access to purchase are the mechanisms that determine the overall sales impact of the app.

Turning now to our propositions: First, regarding customer location, distant customers should particularly appreciate the convenience of retailer apps. The app brings them “closer” to the store at the touch of a button. Near customers already have this convenience because they can easily visit the store. We therefore propose that convenience is more a “problem to be solved” for distant than near customers, and convenience is one of the prime benefits of retailer apps. The superior digital experience afforded by the app might appeal to distant and near customers equally, since they both can access the website directly. We conjecture that the learning costs and habit-change costs are the same for distant vs. near customers. Both need to learn how to use the app, and both need to change their shopping habit by incorporating the retailer app into their routine. The key to the benefits/costs calculus is the convenience the app offers to distant customers, which they now sorely lack. This suggests the retailer app will be more attractive and effective for distant than near customers. In summary, we have the following proposition:

Proposition 1. Distant customers exhibit (a) less wear-out, (b) more state dependence, and (c) a stronger translation of app access to purchase, compared to near customers, all else equal.

Second, regarding channel usage, offline-only customers would be attracted to the convenience and superior digital engagement offered by the app. For customers who already buy online, the app is a useful “add-on” benefit since they are probably currently getting some digital engagement by purchasing online. For offline-only customers, the app is a substantively new

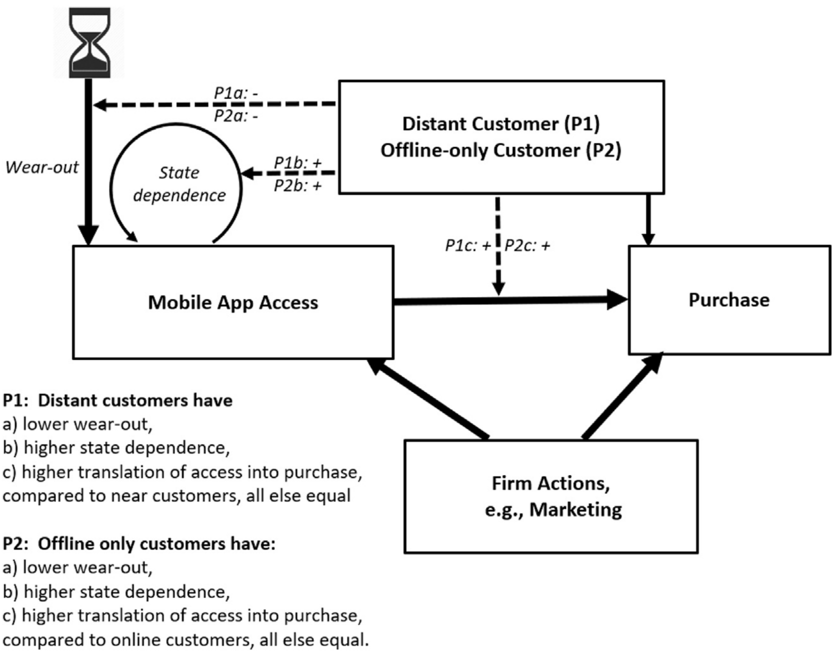

Fig. 1. The process of accessing the app and purchasing.

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channel, so the "superior digital engagement" benefit especially appeals to them. In adopting the mobile app, the offline-only customer becomes more multichannel, which prior research suggests makes them more valuable customers.

Learning costs may be somewhat higher for offline-only customers – they may be less skilled in navigating websites, although apps are typically less complicated. In view of the much higher benefits of convenience and truly new digital engagement for offline-only customers, we propose:

Proposition 2. Offline-only customers exhibit (a) less wear-out, (b) more state dependence, and (c) a stronger translation of app access to purchase, compared to online customers, all else equal.

In summary, we propose that distant and offline-only customers are more likely to value the benefits of the app, while costs are either equal to or balance out with those incurred by near and online customers. Distant and offline-only customers therefore should find the retailer app more appealing; this should be manifested in less wear-out, more state dependence, higher levels of access, and a stronger translation of access into purchase.

4. Data description

4.1. Customer access and purchase data

Our data are from a well-known US apparel retailer that wishes to be anonymous. This high-end retailer has a national online presence through its website, and operates a single brick-and-mortar flagship store in a major metropolitan area. The app, released in 2010, was their first strictly mobile initiative and purely mobile purchase channel. The retailer app features a "product of the day," which highlights a new product from the same product category each day. Thus, every day the consumer who uses the app will see a newly released product from this focal product category. The app also links to the retailer's website so the customer can learn more about its offerings and purchase other goods besides this item. Therefore, from a functional perspective, the app provides two main capabilities: new product introduction and ease of ordering. The app does not use push notifications to notify users of new products. In addition, there is no financial incentive to download the app as products are not discounted on the app.

The retailer serves upscale consumers who purchase a variety of apparel. However, the target group for this app are those especially interested in the focal category. We study consumers who have downloaded the app, as our primary interest is in the drivers of app access and the link from access to purchase. The app is only available to iPhone users. Many users register with the firm by providing an email address. In addition, the firm has a separate email list from purchasers in other channels. To select the sample, we require three stringent conditions: a) email registration on the app must match that in our retailer's database, b) the customer must have purchased at the retailer prior to app introduction and c) the customer must have purchased at the retailer after app introduction. Combined, 629 customers meet these conditions.[3] While this final sample is a bit small for studies like ours, it does allow for a suitable investigation of mobile app usage as we are confident that the data for these consumers is correct and complete.

We study these customers over 77 weeks following the introduction of the app in February 2010. During this time period, downloaders access the app an average of 1.26 times per week, and purchase in 8.5% of the weeks. We do not have complete demographic data, but the nature of the retailer suggests that these are likely high net worth individuals. Table 1 describes the variables used in the analysis and Table 2 offers descriptive statistics.

4.2. Access and purchase predictors

4.2.1. Firm actions

The retailer undertakes online and traditional (offline) advertising not directly aimed at increasing app usage. The bulk of this budget is on traditional offline advertising (93%), a mix of radio, print, television, and billboard campaigns. Most campaigns are short and unique, which makes analysis of any particular campaign difficult. We therefore aggregate the firm's advertising expenditures across these media to measure offline advertising spend. The remaining 7% of the retailer's advertising is on online display advertising. Most of this is general in nature, that is, does not feature the app or involve retargeting. Both online and traditional advertising data are available at the national level.

The retailer runs joint online and offline promotions to spur sales. Discussions with the retailer revealed that most of these promotions are not price-related, but involve a gift-with-purchase or a new product announcement. In addition, there are biannual clearance sales in which some merchandise is discounted. We operationalize $Promotions_t$ as the sum of promotion-days in a given week t. For example, if men's dress shirts are promoted 4 days and women's sunglasses are promoted for 5 days, then this week would have 9 promotion-days. The average week has a total of 4.85 promotion days.

The retailer uses social media to communicate to its customers, particularly Facebook and Twitter. We quantify the number of Facebook or Twitter posts that refer to the retailer's mobile app ($Social\ Posts_t$). They attempt to produce a direct relationship between marketing and access, in contrast to the indirect spillover that might exist for offline/online advertising and promotions. However, they averaged just 0.3 posts per week.

[3] We are also able to continue tracking customers even if they switch mobile phones, as long as they register both devices. In addition, using the iPhone's international mobile station equipment identity number (IMEI), we are able to account for individuals who use an app before they officially register with the firm.

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Table 1
Variable operationalization.

Variable	Operationalization	Source
App accesses	Total number of times the mobile app was accessed in a particular week.	Company
Purchase	A binary variable that is 1 for weeks where a purchase was made in any channel (in-store, online or mobile) and zero otherwise.	Company
Promotions	The number of individual, minor, and major promotion sale days in a particular week. Multi-day promotions are counted by the number of days that the promotion runs.	Company
Social posts	The total number of social posts on Twitter or Facebook in a particular week that specifically refer to the mobile app.	Twitter, Facebook
Online advertising	Total dollars spent on weekly internet display advertising.	TNS
Offline advertising	Total dollars spent on weekly Newspaper, Magazine, Radio, Television and Billboard advertising.	TNS
Distant	A binary variable that is 0 if the individual lives near the store (within the same or adjacent county) and 1 else (and hence is "distant").	Company
Offline-only	A binary variable that is 1 if the individual only bought through the offline channel before the introduction of the app, and 0 else.	Company
Log time since download	The logarithm of the time, in weeks, since the specific user has downloaded the app.	Company
Upgrade(1–3)	A step variable that is 0 before an upgrade of the mobile app, 1 after the upgrade. There are three upgrades of the app during the observation period.	Apple
iOSChange(1–2)	A step variable that is 0 before an upgrade of the iOS operating system, and 1 after the upgrade. There are two upgrades of iOS during the observation period.	Apple
Trend	Time variable which increases linearly with the introduction of the mobile app.	Company
Christmas	A variable which is the sum of the number of days in a particular week when the week falls between Thanksgiving and Christmas.	Company

The firm upgraded the mobile app three times during the sample period. Some of these fixed bugs or increased app reliability, while others added functionality. As with most app upgrades, these upgrades were pushed to the consumer's smartphone directly through the App Store. They are therefore exogenous to the consumer. We capture the impact of these upgrades with separate step dummy variables.

4.2.2. Distance

We measure distance from the store with a binary variable. Individuals who live in the same county as the physical store, or in an adjacent county, are considered near customers ($Distance = 0$), while those who do not are considered distant ($Distance = 1$). While a coarse measure, this operationalization realistically captures the difference between individuals who are able to visit the retail location in a casual or unplanned manner, from those that will require significant effort to visit the store. We do not have other measures for distance, which is a limitation of the data.

Among all customers, 66.3% are distant and 33.7% are near. Not surprisingly, model-free evidence shows significant differences in their purchase and app access behavior. Distant customers have a weekly purchase rate of 6.8%, while near customers have an 11.8% rate; the difference is significant ($p < .001$). Interestingly, distant customers access the app 1.45 times per week, which is significantly ($p < .001$) more than the 0.91 times per week for near customers. This finding is consistent with the idea that for distant customers, the app offers value through digital engagement, as for these customers it is not easy to go to the store and get physically engaged.

4.2.3. Channel usage

We categorize consumers into separate groups based on their prior channel purchases *before* their adoption of the mobile app. Customers who have only purchased from the in-store channel are defined to be offline-only customers ($OfflineOnly = 1$) while those who have ever purchased from the online channel have $OfflineOnly = 0$. Offline-only customers have a significantly lower average weekly purchase rate (7.7%) than online customers (8.7%), and also access the app significantly less frequently (1.11 vs 1.32). Obviously, a more complete model is required to control for other factors that may influence access and purchase.

4.2.4. Dynamic factors

To capture state dependence in access, we use its (one-week) lag.[4] Wear-out is captured by the log of the time since app download.

4.2.5. Other factors

The firm's app is only available on Apple's App Store. This reflects the firm's decision to focus resources on the platform that more closely mirrors the characteristics of its shoppers. iPhone users are known to spend more on mobile apps (Fortune, 2014). In addition, iPhone users have a higher average household income than Android users (Forrester Research, 2011). During the analysis period, Apple's mobile operating system, iOS, was upgraded twice. We capture the effect of these exogenous events through separate step dummy variables. We also account for a trend in access and purchase over time and for Christmas.

[4] We also include a state dependence indicator term for purchase, although not of direct interest in our framework.

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Table 2
Descriptive statistics and correlations.

	Mean	Std. Dev.	Correlations														
			App Accesses	Purchase	Promotions	Social Posts	Online Advertising	Offline Advertising	Distant	Offline-only	Log (Time Since Download)	Upgrade1	Upgrade2	Upgrade3	iOSChange1	iOSChange2	Trend
App accesses	1.260	2.123															
Purchase	0.085	0.279	0.049**														
Promotions	4.850	4.988	0.030**	0.019**													
Social Posts	0.310	0.875	0.071**	−0.005	−0.061**												
Online advertising	$6.306	$5.489	0.150**	0.010*	0.036**	0.073**											
Offline advertising	$81.645	$49.533	−0.011*	0.013**	0.299**	0.015**	−0.044**										
Distant	0.663	0.473	0.120**	−0.085**	0.000	−0.002	−0.005	0.001									
Offline-only	0.257	0.437	−0.043**	−0.016**	−0.001	0.000	0.003	−0.002	−0.145**								
Log (time since download)	3.330	0.835	−0.269**	−0.045**	−0.058**	−0.266**	−0.432**	0.049**	−0.002	0.008							
Upgrade1	0.800	0.400	−0.235**	−0.018**	−0.055**	−0.218**	−0.458**	0.011*	0.010*	−0.009	0.682**						
Upgrade2	0.780	0.416	−0.224**	−0.016**	0.002	−0.222**	−0.422**	0.091**	0.010*	−0.009	0.681**	0.933**					
Upgrade3	0.700	0.457	−0.215**	−0.010*	0.104**	−0.323**	−0.298**	0.332**	0.008	−0.010*	0.684**	0.768**	0.823**				
iOSChange1	0.830	0.372	−0.240**	−0.023**	−0.020**	−0.092**	−0.546**	0.066**	0.009	−0.008	0.678**	0.892**	0.832**	0.685**			
iOSChange2	0.120	0.325	−0.102**	−0.010*	−0.137**	−0.130**	0.150**	−0.212**	0.000	−0.004	0.354**	0.185**	0.198**	0.240**	0.165**		
Trend	52.840	2.985	−0.245**	−0.017**	−0.073**	−0.296**	−0.301**	0.050**	0.005	−0.010*	0.808**	0.726**	0.751**	0.811**	0.681**	0.540**	
Christmas	0.390	1.533	−0.037**	0.012*	0.045**	−0.089**	−0.018**	0.396**	0.003	−0.001	0.054**	0.127**	0.136**	0.166**	0.113**	−0.094**	0.018**

$N = 41{,}892$.

** Correlation is significant at the 0.01 level (2-tailed).

* Correlation is significant at the 0.05 level (2-tailed).

5. Model

We draw on our framework (Fig. 1) to specify statistical models of the consumer decision to access the retailer's mobile app and to purchase. We discuss these models next.

5.1. Access model

$AppAccess_{it}$ is the number of times customer i accesses the app in week t. We model $AppAccess_{it}$ as a function of its drivers[5]:

$$\begin{aligned} AppAccess_{it} = {} & \alpha_i + \beta_{1i} AppAcces_{i,t-1} + \beta_{2i} Log\_TimeSinceDownload_{it} + \beta_{3i} Purchase_{i,t-1} + \beta_{4i} OfflineAd_t + \beta_{5i} OnlineAd_t \\ & + \beta_{6i} Promotions_t + \beta_{7i} SocialPosts_t + \sum_{j=1}^{3} \beta_{7+j,i} Upgrade_{j,t} + \sum_{k=1}^{2} \beta_{10+k,i} iOSUpgrade_{k,t} + \beta_{13i} Trend_t \\ & + \beta_{14i} Christmas_t + \varepsilon_{1it} \end{aligned} \tag{1}$$

All response parameters are customer-specific, reflected in the subscripts i. We explain how we model the moderating roles of distance and channel usage below. The parameter α_i is the fixed effect for customer i that captures any unobserved between-customer difference in the level of access. The fixed effects in the model imply there is no need to include main effects of time-invariant customer characteristics. $AppAccess_{i,\ t-1}$ captures access state dependence and $Log\_TimeSinceDownload_{it}$ captures wear-out, as discussed above. $Purchase_{i,\ t-1}$ measures purchase feedback effects.

$OfflineAd_t$ is the retailer's spend on offline advertising and $OnlineAd_t$ is the spend on online advertising (display ads). $Promotions_t$ measures promotions in week t, and $SocialPosts_t$ is the number of Tweets and Facebook posts the company issues about the app.

Variables that denote changes in the app are measured by $Upgrade_{j,\ t}$, a step dummy for upgrade j ($j = 1,..,3$), and $iOSUpgrade_{k,\ t}$, a step dummy for upgrade k to the iPhone and iPad operating system ($k = 1,2$). The access model includes the dynamics shown in Fig. 1.

Finally, we include $Trend_t$ (1 in the first week of the data, 2 in the second week, etc.) to represent customer-specific trends in access (via its heterogeneous response parameter). $Christmas_t$ is the sum of the number of days in a particular week when the week is between Thanksgiving and Christmas, as these holidays may influence app access.

5.2. Purchase model

We use a probit model for customer i's purchase decision in week t, which posits an unobserved utility of purchase (U^*). The customer purchases across any channel if $U^*_{it} > 0$ and is modelled as:

$$U^*_{it} = \gamma_i + \delta_{1i} AppAccess_{it} + \delta_{2i} OfflineAd_t + \delta_{3i} OnlineAd_t + \delta_{4i} Promotions_t + \delta_{5i} Purchase_{i,t-1} + \delta_{6i} Trend_t + \delta_{7i} Christmas_t + \varepsilon_{2it} \tag{2}$$

Again, all parameters are customer-specific, capturing heterogeneity. The fixed effect γ_i is the intercept for customer i, capturing unobserved differences across customers in their purchase utility. The parameter δ_{1i} captures the probability that a mobile app access will turn into a purchase. This will let us determine if accessing the app increases purchase likelihood, which we posit is a key consequence of the engagement entailed in accessing the app. The other variables are the same as previously defined. To account for unobserved shocks affecting both access and purchase, we allow for a correlation between the error term ε_{1it} from Eq. (1) and ε_{2it} from Eq. (2). An alternative model would include purchase amount. However, due to the sparseness of purchases and large volatility of purchase size, we focus solely on purchase incidence.

5.3. The moderating role of distance

Our propositions imply that certain parameters in the access and purchase models are systematically moderated by the customer's location (near or distant) and pre-app channel usage (offline-only or some online). While we allow all parameters to be fully heterogeneous across customers, for those parameters where we expect moderating effects we include these two moderators as covariates. For example, propositions P1c and P2c imply that the effect of app access on purchase is stronger for distant customers and for offline-only customers. Hence we model it as $\delta_{1i} = \overline{\delta}_1 + \overline{\delta}_{1,1} Distant_i + \overline{\delta}_{1,2} OfflineOnly_i + v_{0i}$, where we expect that $\overline{\delta}_{1,1}>0$ and $\overline{\delta}_{1,2}>0$. We use similar specifications for $\beta_{1i}$and β_{2i}. We assume that all other heterogeneous response parameters in Eqs. (1) and (2) are distributed around a hypermean, so that for any other variable k: $\delta_{ki} = \overline{\delta}_k + v_{ki}, \beta_{ki} = \overline{\beta}_k + u_{ki}$.

[5] Noting the count nature of the dependent variable we tried alternative models including Poisson and Negative Binomial. These provided similar results to the focal model. However, count models with autoregressive regressors required to capture state dependence can be unstable and there is no established solution (Cameron & Trivedi, 2013, p. 281). Since model (1) is a panel data model with a lagged dependent variable, we also considered the Arellano-Bond estimator. It again yields very similar results, in line with the notion that for panels with a large T (e.g., $T > 30$) there is hardly any difference between Arellano-Bond estimates and fixed-effect estimates (Roodman, 2006).

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5.4. Endogeneity and identification

We reiterate that this analysis is based only on adopters of the app, and hence we do not deal with adopters versus non-adopters (and the associated selection issue this entails). However, one potential endogeneity issue is that unobserved time-invariant customer characteristics may drive both app access and the propensity to purchase. In particular, some customers may have a higher interest in the store, leading to more purchases and higher app access. To safeguard against using this type of cross-sectional variation for inferring the effect of app access on purchasing, Eq. (2) includes customer-specific fixed effects. These fixed effects (estimated with Bayesian methods) absorb any cross-sectional endogeneity. Hence, we only use within-customer variation in app usage and link it with within-customer variation in purchase rates.

However, within-customer app access may be partly endogenous. For example, a given consumer may plan to make a purchase and will open the retailer's mobile app to see what product is available. In this scenario, app usage correlates with purchase but did not cause the purchase. To account for this form of longitudinal endogeneity (within customers), we employ instrumental variables (IVs) that explain exogenous longitudinal variation in app usage but do not relate directly to purchase. The access equation naturally contains these IVs. First, it includes the five dummies representing upgrades to the app and to the operating system. These updates influence app access (positively or negatively, depending on the quality of the update) and hence satisfy the relevance criterion for IVs. However, these app upgrades are unlikely to have a direct effect on purchase as they do not affect the quality or value of the offering itself. In addition, these upgrades were pushed to the consumer's smartphone directly through the App Store and they are exogenous to the consumer's app usage or purchases. Hence we argue that these IVs are valid, i.e., they satisfy the exclusion restriction.

Another IV in Eq. (2) is the time since download, measuring the wear-out effect of the app. Our argument for the validity of this IV is that when the consumer has just downloaded the app, the initial excitement will cause the consumer to access the app. This engages the consumer, at least for the time being, and this engagement will lead to a (temporarily) enhanced purchase rate. Over time, the novelty of the app wears off, and the consumer is less engaged and purchases less. Hence the effect of time since download on purchase must go through app access, which makes it a valid IV. In other words, there is nothing intrinsic that changes in the retailer's offering from the moment a consumer installs the app. The Sanderson-Windmeyer multivariate F-test shows that the IVs are sufficiently strong ($p < .01$).

Given the nonlinear nature of the purchase model (and its Bayesian estimation), we cannot conduct a Sargan test or similar to test for instrument validity. In addition, scholars such as Rossi (2014, p. 665) argue that “there is no way to test the validity of instruments and, thus, the only recourse is an economic argument regarding why a specific instrument is exogenous to the determinants of demand.” In line with Rossi, Allenby, and McCulloch (2005), we directly control for endogeneity by including the above IVs in the access equation and by correlating its error term with the error term of the purchase eq. (1). Online Appendix A discusses details.

Another identification issue would arise if there were autocorrelation in the residuals of Eqs. (1) and (2). However, we find that there is no evidence of autocorrelation in either the purchase equation's generalized residuals nor in the access equation's residuals. Specifically, we use Durbin's h (distributed standard normal under the null of no autocorrelation) because the models include lagged dependent variables. The error autocorrelation coefficient for access is −0.07 and Durbin's h is −0.59 ($p > .1$). The autocorrelation in the generalized residuals of the purchase model equals 0.01 and Durbin's h is 0.06 ($p > .1$). Hence we find no evidence for autocorrelation in the access model or in the purchase model. Therefore, our system of equations boils down to a triangular system where current access drives current purchase but not vice versa and where their errors have no autocorrelation. For identification purposes, we need at least one exogenous variable in the access equation. To be on the safe side and as explained above, we include six exogenous variables that serve as instrumental variables, and correlate the contemporaneous errors of the two equations.

We address potential endogeneity of online and offline advertising in the access and purchase equations using control functions (e.g., Petrin & Train, 2010). This is appropriate because the purchase equation has a binary dependent variable. For the access equation, the control function approach is equivalent to 2SLS. The control function approach estimates first-stage regressions for each type of advertising, and includes their residuals as covariates in Eqs. (1) and (2). These regressions include two sets of IVs. The first is quarterly advertising costs for TV advertising, radio advertising, print advertising, and internet advertising (source: U.S. Bureau of Labor Statistics). Costs are likely to influence advertising expenditures, satisfying relevance. They also satisfy the exclusion restriction as these costs are unlikely to cause access or purchase behavior directly. The second set is the total advertising expenditure (TV, magazine, newspaper, and online display) by retailers that are not direct competitors of the focal retailer. These expenditures may be correlated with the focal retailer's advertising patterns due to industry practice in advertising timing, but should have no impact on access or purchase for the focal firm). Sanderson-Windmeyer multivariate F-tests confirm the strength of the IVs for both online and offline advertising ($p < .01$). Online Appendix A provides more estimation details and Table B1 in the Online Appendix B shows the first-stage regression results.

The models include other marketing variables: promotions and app-related social posts. We argue that these are unlikely to be endogenous. We discussed the promotion schedule with company management, who were clear that the promotional calendar is determined well in advance (between a quarter and a year ahead) and are not based on week-to-week unobserved demand shocks, mitigating endogeneity concerns. As for social posts, the company uses Twitter and Facebook to post messages that relate to the app. The Tweets go to all Twitter followers of the company, and hence they are not based on customer-specific unobserved factors.

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5.5. Model estimation

We estimate Eqs. (1) and (2) jointly with normally distributed, correlated errors, using hierarchical Bayesian estimation (Gibbs sampling) and uninformative priors. Models (1) and (2) constitute a binomial-continuous hierarchical recursive system. We draw on Chib and Greenberg (1995) to estimate the system, and use data augmentation to account for the 0/1 nature of the purchase equation (Albert and Chib 1993). To estimate the covariance matrix of the errors we draw on Edwards and Allenby (2003). Online Appendix A details the estimation procedure.

6. Results

We now discuss results for the access and purchase models. Previewing the key findings: Compared to near customers, distant customers exhibit (a) similar wear-out, (b) more state dependence, and (c) a stronger translation of app access to purchase. Offline-only customers exhibit (a) similar wear-out, (b) similar state dependence, and (c) a stronger translation of app access to purchase, compared to online customers, all else equal.

6.1. Determinants of app access

Table 3 shows the results of the full model, and an additional model without interactions, included to show the robustness of the main effects. The full app access model (Eq. (1)) shows good fit with an R^2 of 0.834. We first discuss the significant control variables. Offline advertising exerts a positive impact on access ($\overline{\beta}_4 = 0.006$, $p < .10$), suggesting a spillover or cross effect (e.g., Dinner, Van Heerde, & Neslin, 2014). Promotions also encourage app access ($\overline{\beta}_6 = 0.008$, $p < .05$). From a practical standpoint, offline advertising and promotions are levers managers can use to drive app usage. Upgrades yield mixed results, with one upgrade lifting access (e.g., Upgrade2, $\overline{\beta}_9 = 0.034$, $p < .05$), but the others are insignificant, albeit slightly negative. These findings show that upgrades may not have the desired effect, perhaps by introducing new glitches or alienating users. Both iOS operating system upgrades have detrimental effects on app usage (iOSChange1, $\overline{\beta}_{11} = -0.050$, $p < .05$; iOSChage2, $\overline{\beta}_{12} = -0.007$, $p < .10$). This could be due to an increase in computing demands on the customer's mobile device.

Table 3
Model results for accessing the mobile app: posterior distribution of the standardized hyperparameters.

Fixed effects	Symbol	Proposition	Main Effects Only Included	2.5th pctl	5th pctl	Full Model median Included	95th pctl	97.5th pctl
Consumer Factors								
Lagged App Access	$\overline{\beta}_1$		0.293**	0.220	0.227	**0.264****	0.299	0.305
× Distant	$\overline{\beta}_{1,1}$	P1b: +		0.000	0.005	**0.045****	0.085	0.094
× Offline-only	$\overline{\beta}_{1,2}$	P2b: +		−0.069	−0.059	**−0.009**	0.037	0.043
Log time since download	$\overline{\beta}_2$		−0.129**	−0.168	−0.160	**−0.130****	−0.102	−0.093
× Distant	$\overline{\beta}_{2,1}$	P1a: +[a]		−0.032	−0.026	**−0.002**	0.024	0.030
× Offline-only	$\overline{\beta}_{2,2}$	P2a: +[a]		−0.022	−0.015	**0.014**	0.042	0.046
Lagged Purchase	$\overline{\beta}_3$		−0.003	−0.009	−0.008	**−0.003**	0.002	0.002
Marketing Variables								
Offline Advertising	$\overline{\beta}_4$		0.005*	−0.001	0.000	**0.006***	0.011	0.013
Online Advertising	$\overline{\beta}_5$		0.004	−0.006	−0.004	**0.003**	0.012	0.014
Promotions	$\overline{\beta}_6$		0.008**	0.003	0.004	**0.008****	0.012	0.013
Social Posts	$\overline{\beta}_7$		0.002	−0.003	−0.002	**0.002**	0.007	0.008
App Construction Factors								
Upgrade1	$\overline{\beta}_8$		−0.008	−0.023	−0.022	**−0.008**	0.006	0.009
Upgrade2	$\overline{\beta}_9$		0.033**	0.018	0.020	**0.034****	0.046	0.048
Upgrade3	$\overline{\beta}_{10}$		−0.010	−0.026	−0.023	**−0.011**	0.001	0.002
iOSChange1	$\overline{\beta}_{11}$		−0.049**	−0.065	−0.063	**−0.050****	−0.039	−0.037
iOSChange2	$\overline{\beta}_{12}$		−0.006*	−0.013	−0.012	**−0.007***	−0.001	0.000
Other controls								
Trend	$\overline{\beta}_{13}$		−0.010	−0.036	−0.30	**−0.008**	0.017	0.020
Christmas	$\overline{\beta}_{14}$		−0.014**	−0.020	−0.019	**−0.014****	−0.010	−0.009
Control Function Online Advertising			0.008	−0.016	−0.013	**0.004**	0.020	0.023
Control Function Offline Advertising			0.011**	0.002	0.003	**0.012****	0.021	0.022
Number of Observations		41,892						
R^2 for full model		0.834						

Values in bold highlight the median values for each coefficient.
** 95% posterior density excludes zero.
* 90% posterior density excludes zero.

Christmas is associated with lower access ($\overline{\beta}_{14} = -0.014$, $p < .05$). During Christmas season, customers may be more goal-directed and hence go directly either to the store or website. The control function for offline advertising is significant (coefficient = 0.012, $p < .05$), which suggests that offline advertising in the access model is endogenous and therefore needs the control function to compute a consistent estimate of the impact of offline advertising on access.

Turning to the focal effect estimates, app access is significantly driven by dynamics. Observing the effects of a model with only main effects, we see there is significant state dependence as lagged app access has a positive effect ($\overline{\beta}_1 = 0.293$, $p < .05$). Over time, however, app usage becomes less and less frequent, evidenced by a negative effect main effect of time since download ($\overline{\beta}_2 = -0.129$, $p < .05$).

Moving back to the model with interactions, we find that distant customers have a positive interaction with lagged access ($\overline{\beta}_{1,1} = 0.045$, $p < .05$), supporting P1b and suggesting that distant customers find the app helpful and hence current usage enhances the likelihood of future usage. Second, distant customers have a similar wear-out to customers that are near ($\overline{\beta}_{2,1} = -0.002$, *n.s.*), which does not provide support for P1a.

We now turn to the coefficients that relate to propositions about offline-only customers. We see similarities between offline-only customers and those who use the online channel regarding wear-out on access ($\overline{\beta}_{2,2} = 0.014$, *n.s.*) and state-dependence of mobile access ($\overline{\beta}_{1,2} = -0.009$, *n.s.*). These results do not provide support for P2a or P2b.

In summary, compared to near customers, distant customers' access is stickier (shows more state dependence) but wear-out rates are similar. Offline-only and online customers have similar access behavior across all metrics. We next discuss how app access and other factors drive purchase probability.

6.2. Determinants of purchase

Table 4 displays estimated hyperparameters for the purchase model (eq. (2)). Focusing on the control variables first, we find that Offline advertising has a positive effect on purchase probability ($\overline{\delta}_2 = 0.024$, $p < .05$). There is a negative overall trend in the purchase rate ($\overline{\delta}_6 = -0.032$, $p < .05$) and a small negative Christmas effect ($\overline{\delta}_7 = -0.010$, $p < .05$), although the effect is slightly positive in the model with main effects only. The control function for online advertising is significant (coefficient = −0.018, $p < .05$), which suggests that online advertising in the purchase model is endogenous. Oddly, online advertising has a tiny negative effect ($\overline{\delta}_3 = -0.009$, $p < .05$), but this is not the case in the model with main effects only.

As for the key customer variables, we see the main effect of access on purchase is positive ($\overline{\delta}_1 = 0.041$, $p < .05$). However, in the full model we see that the effect of access on purchase is significantly higher ($\overline{\delta}_{1,1} = 0.020$, $p < .05$) for distant customers, supporting P1c. For offline-only customers, the effect of access on purchase is also significantly higher ($\overline{\delta}_{1,2} = 0.016$, $p < .05$), supporting P2c. These results suggest that the engagement generated by accessing the app strongly enhances the inclination to purchase.

To summarize, the key result from the purchase equation is the translation of app access into purchase is larger for distant and offline-only customers, compared to near and online customers respectively. This suggests that distant and offline-only customers find the app more engaging, generating larger purchase probabilities.

Table 4
Model results for probit model for purchases: posterior distribution of the standardized hyperparameters.

	Symbol	Proposition	Main Effects Only	2.5th pctl	5th pctl	Full Model median	95th pctl	97.5th pctl
Fixed effects			Included			Included		
Effect of mobile app								
App access	$\overline{\delta}_1$		0.041**	0.023	0.024	**0.035****	0.051	0.052
× Distant	$\overline{\delta}_{1,1}$	P1c: +		0.008	0.009	**0.020****	0.029	0.029
× Offline-only	$\overline{\delta}_{2,2}$	P2c: +		0.010	0.011	**0.016****	0.022	0.023
Marketing variables								
Offline advertising	$\overline{\delta}_2$		0.020**	0.020	0.020	**0.024****	0.029	0.030
Online advertising	$\overline{\delta}_3$		0.013**	−0.012	−0.012	**−0.009****	−0.004	−0.003
Promotions	$\overline{\delta}_4$		0.015**	0.005	0.009	**0.017****	0.017	0.019
Other controls								
Lagged purchase	$\overline{\delta}_5$		0.027**	0.003	0.003	**0.006****	0.014	0.014
Trend	$\overline{\delta}_6$		−0.027**	−0.037	−0.036	**−0.032****	−0.028	−0.027
Christmas	$\overline{\delta}_7$		0.002*	−0.014	−0.013	**−0.010****	−0.004	−0.004
Control function online advertising			−0.002	−0.022	−0.021	**−0.018****	−0.015	−0.014
Control function offline advertising			−0.006	−0.007	−0.009	**0.000**	0.006	0.007
Number of Observations = 41,892								
Sensitivity = true positives/positives = 0.726								
Specificity = true negatives/negatives = 0.738								
Balanced accuracy = average of sensitivity and specificity = 0.732								

Values in bold highlight the median values for each coefficient.

6.3. Heterogeneity in customer behavior

To develop further insights, we classify customers using our two focal moderators: distance and offline-channel choice. Because distant vs near and offline-only vs online channel usage are binary, we can create four customer groups, as in Table 5 (first row). Of these customers, 22.4% are nearby but also purchase online. The next, and largest, group (52.3%) are distant and purchase online. The smallest group (11.3%) only purchase offline and are near the store. The final group (14.0%) only purchase offline and are distant. These customers are unique in that they clearly undertake a serious effort to visit the store.

Fig. 2 shows how the wear-out effect differs between the four groups. To create the baseline access levels in Fig. 2, we used each customer's fixed effect. While offline-only and online customers access the app equally often, Fig. 2 shows that distant customers access the app more frequently than near customers, in line with the model-free evidence shown before. It is also clear that app access wears out at the same rate for all groups.

Fig. 3 shows the impact of access on the increase in purchase probability ("lift") for all four customer groups. This figure shows that the distant/offline-only customers experience the highest growth in impact, as exhibited by its steepest response curve. Near/offline-only is next steepest, with distant/online not far behind; clearly near/online customers respond the least to increased app access.

Table 5 provides a more complete view of the app usage and purchase process by calculating long-term elasticities ("η"). We start with the estimated Models (1) and (2). Then we increase a variable by 1% in period t and study how this drives access and purchases in periods t, $t+1$, $t+2$, etc., for each of the $N = 629$ customers. For each customer, we use 200 draws of their individual posterior parameter distribution to account for parameter heterogeneity and uncertainty. Within each draw for each customer, we average across 100 replications to account for the randomness of the purchase decision.

Table 5 quantifies our interpretations of the graphs in Fig. 3. Distant/Offline-only customers are most responsive in their purchase response to a 1% increase in access ($\eta = 0.119$). Distant/online and near/offline-only respond slightly less (0.084 and 0.055, respectively), and near/online customers respond the least (0.038). Fig. 4 shows heterogeneity in these numbers, which the most heterogeneity exhibited for the distant/offline-only customers.

Table 5 shows that the direct effect of offline advertising on purchase is strong, ranging from 0.076 to 0.091 across the four groups. Table 5 provides additional insight by displaying elasticities of access with respect to marketing. We see that driving app usage is difficult, with rather modest elasticities of around 0.026 for offline advertising, and around 0.017 for promotion, the two marketing variables that have a significant impact on access.

6.4. Economic value of the app

We now explore the economic value of the app to the retailer among the customers who have downloaded the app. Importantly, we assess the value of incremental access on purchase behavior within this group, not the difference between adopters and non-adopters (which we do not model anyway).

Many consumers access the app around 0, 1, 2 or 3 times a week, with a mean of 1.26 and a standard deviation of 2.12 (Table 2). Our simulations take into account this variation by simulating purchases for three scenarios: (I) access = 0; (II) access = observed access, with a mean of 1.26, and (III) access is 50% higher than observed, with a mean of 1.89.

The difference between the current access scenario (II) and the zero access scenario (I) is the lift in purchase probability that can be attributed to the app, in line with attribution modelling (e.g., Danaher & Van Heerde, 2018). The difference between the current scenario (II) and scenario (III) could result from the retailer improving the functionality of the app, making app access more attractive. Scenario (III) requites the consumer to access the app just 0.63 times more often per week (1.89–1.26), or just less than two more times every three weeks. This is a very modest increase that is entirely within the range of the data.

Table 5
Elasticities of access and purchases across customer groups.

Descriptive statistics	Total sample ($N = 629$)	Near, Online customers (22.4% of sample)	Distant, Online customers (52.3% of sample)	Near, Offline-only Customers (11.3% of the sample)	Distant, Offline-only Customers (14.0% of the sample)	p-value for difference
LT elasticity app access due to 1% increase in offline advertising	0.026 (0.014)[a]	0.029 (0.017)	0.024 (0.014)	0.026 (0.020)	0.025 (0.018)	0.896
LT elasticity app access due to 1% increase in promotion	0.017 (0.006)	0.018 (0.008)	0.017 (0.006)	0.018 (0.010)	0.017 (0.008)	0.961
LT elasticity app access due to 1% increase in app access	1.398 (0.018)	1.360 (0.036)	1.423 (0.024)	1.300 (0.045)	1.459 (0.051)	0.024*
LT elasticity purchase probability due to 1% increase in offline advertising	0.083 (0.010)	0.076 (0.010)	0.085 (0.010)	0.080 (0.010)	0.091 (0.011)	0.000*
LT elasticity purchase probability due to 1% increase in promotion	0.017 (0.008)	0.014 (0.007)	0.018 (0.008)	0.016 (0.008)	0.021 (0.008)	0.000*
LT elasticity purchase probability due to 1% increase in app access	0.071 (0.013)	0.038 (0.009)	0.084 (0.017)	0.055 (0.008)	0.119 (0.018)	0.000*

[a] Standard deviations across draws in brackets.
* Difference in means is significantly different from zero at the 0.05 level (2-tailed).

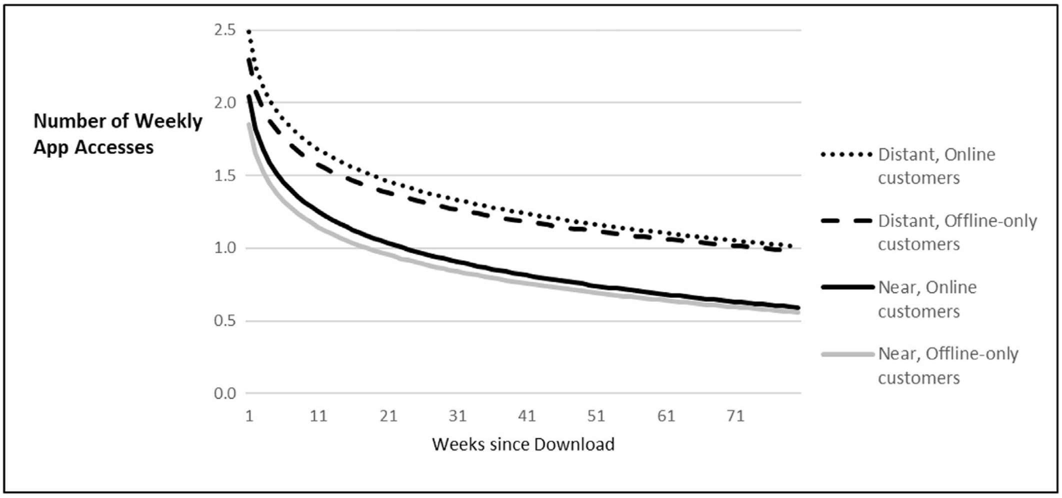

Fig. 2. App access: the wear-out effect.

For each scenario, we calculate for each customer the expected purchase likelihood for every week, using the observed covariates for each consumer and 200 draws of the consumer-specific vector of intercepts and consumer-specific vector response parameters. We set Access = 0 or Access +50% to create Scenarios I and III.

Table 6 shows that at observed covariates and current Access levels (Scenario II), customers average an expected weekly purchase probability of 0.0936. For Scenario I (no access) this probability equals 0.0892, while in Scenario III (50% increase in Access), it is 0.0960. While these are the results across all customers, there is considerable heterogeneity among the four groups, with the distant/offline-only group's purchase probability going up by close to 15% (0.0556 to 0.0639).

In Columns 4–6 we calculate the expected annual number of purchases per customer for the three scenarios. Columns 7–9 show the expected annual revenue per customer, assuming an average transaction of $100 (reasonable for this high-end retailer). Columns 10–12 display total expected annual revenue for each Scenario, assuming there are 100 K customers (to generate a realistic magnitude of revenue). The retailer itself is quite large, with over 500 K unique customers during the 5 years before. Given the ubiquity and simplicity of mobile apps today, we do not believe it is out of line for the retailer to have 100 K users for a mobile app with a broad appeal.

Columns 13 and 14 compare Scenario II (current Access level) to I (no Access) and to III (50% increase in Access). Column 13 shows total annual additional revenue attributable to app access is $2.28 M (a 4.9% increase). Much of this gain is due to distant and offline-only customers ($0.38 M, a 9.5% increase for this group, or 17% of the total additional revenue). The largest absolute impact comes from distant and online customers ($1.37 M, a 6.8% increase), because of the large number of customers in this group (52% of the sample). Column 14 shows the potential for an additional $1.27 M increase in revenue if app usage can be

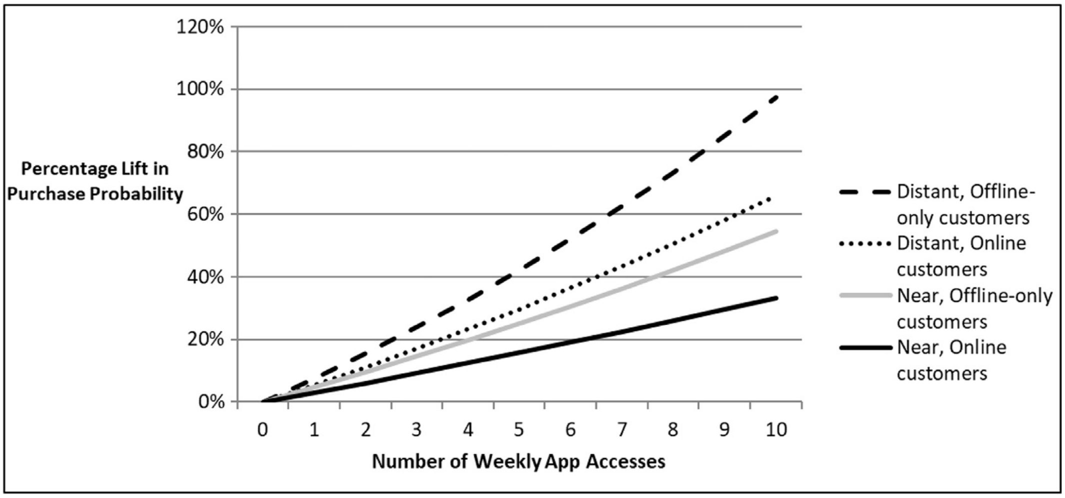

Fig. 3. Direct impact of app access on lift in purchase probability.

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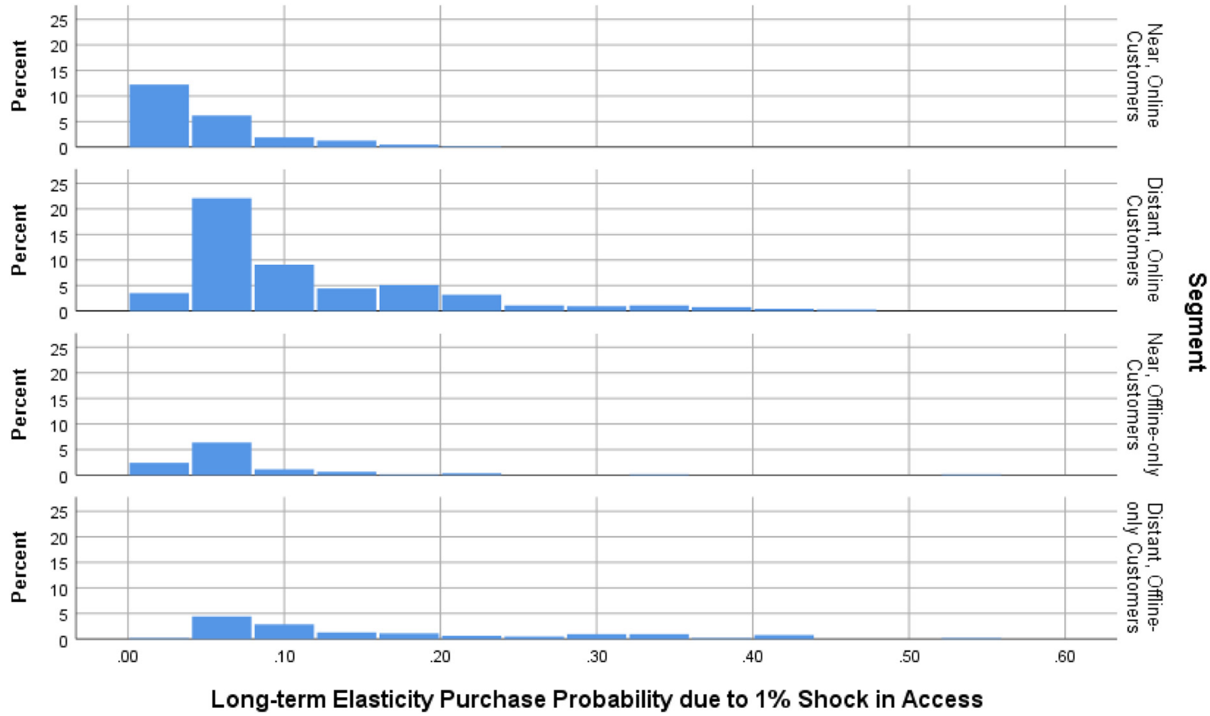

Fig. 4. Heterogeneity in impact of app access on purchase probability.

increased by 50%. While near/online customers show a modest value increase (+0.9%), distant/offline-only-customers have a substantive expected revenue gain of $.22 M (+5%).

These calculations depend on the assumptions that are made, but they are probably on the conservative side as far as the average spend per customer and the number of customers are concerned. The calculations show that a retailer mobile app has great potential to lift the company's revenues substantially, especially from distant customers.

6.5. Robustness checks

We ran several robustness checks, details of which are available on request. First, to show that we obtain similar insights with a much simpler model, we ran a probit model with random intercepts and direct multiplicative interactions between the two moderators and the relevant variables (e.g., time since download in the access model). We obtain the exact same insights on the propositions with this model compared to the full model.

Second, to rule out that our results are purely driven by cross-sectional differences, we ran separate probit purchase models for each customer. For each customer, we divide the parameter estimate for the effect of access on purchase utility by its standard error to obtain a *Z*-value. Next, we combine the Z-values across customers based on Rosenthal's method of added Zs (Rosenthal 1991). The combined Z-value equals 6.282; $p < .0001$, which again shows that there is a significant positive effect of access on purchase utility.

Third, we included Time Since Download (TSD) in the Purchase model. The coefficient for TSD is strongly negative. We hesitate to interpret this as decreasing attitudes toward the retailer. More importantly, although the main effect of access becomes n.s., the interactions with distant and offline-only channel usage remain strongly positive. Therefore, our key hypothesis and results – that the app is more successful at engaging distant and offline-only customers – hold up.

Fourth, we estimated a model without any endogeneity correction. That is, we restrict the correlation in the error term of the access model and purchase utility model to zero and exclude the control function terms for online and offline advertising from both models. As Online Appendix C shows, the focal effects (expressed in the propositions) are replicated in terms of signs and significance, although with slightly different effect sizes.

7. Summary and managerial implications

7.1. Summary

Mobile apps have emerged as an extensively-used tactic by which retailers aim to increase customer engagement and thus increase customer value. We investigate for which customers the app is most likely to be effective. We focus on two key customer

Table 6
Illustration of the Economic Value of the App.

	Expected purchase probability per week			Expected annual # purchases per customer			Expected annual revenue per customer			Expected revenue across customers			Revenue Differences	
							Assumption: $100 per transaction			Assumption: 100,000 customers: Near, online customers: 22% Distant, Online customers: 52% Near, Offline-only customers: 11% Distant, Offline-only customers:14%			Current Access versus No Access	50% More Access versus Current Access
Column:	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Scenario:	I Access = 0	II Current Access	III Access +50%	I Access = 0	II Current Access	III Access +50%	I Access = 0	II Current Access	III Access +50%	I Access = 0	II Current Access	III Access +50%	Current access (col. 11) – Access = 0 (col. 10)	Access +50% (col. 12) – Current access (col. 11)
All customers	0.0892	0.0936	0.0960	4.64	4.87	4.99	$464	$487	$499	$46.39 M	$48.67 M	$49.94 M	$2.28 M	$1.27 M
	(0.0014)	(0.0013)	(0.0015)	(0.07)	(0.07)	(0.08)	($7)	($7)	($8)	($1.34 M)	($1.33 M)	($1.41 M)	[+4.9%]	[+2.6%]
Near, Online customers	0.1350	0.1375	0.1387	7.02	7.15	7.21	$702	$715	$721	$15.74 M	$16.02 M	$16.17 M	$0.28 M	$0.15 M
	(0.0032)	(0.0032)	(0.0032)	(0.16)	(0.17)	(0.17)	($16)	($17)	($17)	($0.37 M)	($0.37 M)	($0.38 M)	[+1.8%]	[+0.9%]
Distant, Online customers	0.0742	0.0793	0.0821	3.86	4.12	4.27	$386	$412	$427	$20.19 M	$21.56 M	$22.33 M	$1.37 M	$0.77 M
	(0.0019)	(0.0018)	(0.0020)	(0.10)	(0.09)	(0.10)	($10)	($9)	($10)	($0.51 M)	($0.48 M)	($0.54 M)	[+6.8%]	[+3.6%]
Near, Offline-only customers	0.1094	0.1135	0.1157	5.69	5.90	6.02	$569	$590	$602	$6.42 M	$6.66 M	$6.79 M	$0.24 M	$0.13 M
	(0.0041)	(0.0042)	(0.0042)	(0.22)	(0.22)	(0.22)	($22)	($22)	($22)	($0.24 M)	($0.24 M)	($0.25 M)	[+3.8%]	[+1.9%]
Distant, Offline-only customers	0.0556	0.0608	0.0639	2.89	3.16	3.32	$289	$316	$332	$4.04 M	$4.43 M	$4.65 M	$0.38 M	$0.22 M
	(0.0030)	(0.0031)	(0.0033)	(0.16)	(0.16)	(0.17)	($16)	($16)	($17)	($0.22 M)	($0.23 M)	($0.24 M)	[+9.5%]	[+5.0%]

Standard deviation across draws are in parentheses (); percentage differences in brackets [].

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descriptors that are particularly relevant in today's multichannel, online-oriented retailing environment– *distance* from the store of the customer's residence, and *current channel usage* (offline-only vs. online). We propose that distant and offline-only customer have needs that aren't being met, be it convenient interaction with the retailer (distant customers) or digital engagement (offline-only customers). Therefore, the app should be most effective among these customers. To test these propositions, we model the process by which customers are induced to access the app, and the extent to which this access translates into purchase.

The specific propositions and results are summarized in Table 7. We find distant customers exhibit (a) similar wear-out, (b) more state dependence, and (c) a stronger translation of app access to purchase compared to near customers. Offline-only customers exhibit (a) similar wear-out, (b) similar state dependence, and (c) a stronger translation of app access to purchase, compared to online customers, all else equal. We discuss key findings here:

- *The translation of app access into purchase is stronger for distant and offline-only customers*

This suggests that distant and offline-only customers find their interactions with the app to be more valuable, which, although we cannot measure it directly, implies they find these actions more engaging. Table 6 suggests the managerial importance of the finding. Accessing the app at the distant and offline-only customers' current access rate increases revenues by 9.5% compared to if they were not accessing the app; the increase for online/near customers is only 1.8%. If the retailer could increase access by 50%, there would be a further 5% increase in revenues for distant/offline-only customers. Clearly the app provides a way to increase distant customer engagement and make it count.

- *Distant customers access the app more frequently than near customers; offline-only customers access the app at the same rate as online customers do.*

This result suggests that the digital engagement offered by the app is especially important for distant customers who lack easy access to the physical engagement offered by the store. For distant customers, the app may serve as a substitute for directly visiting the website or for incurring the costs of traveling to the store.

- *State dependence is stronger for distant customers than for near customers.*

State dependence measures the extent to which accessing the app now increases the access rate in the future. The reasons for this range from habit formation to cognitive learning; as in all customer-level models, we cannot ascertain which mechanism is more at work. However, one possibility is that distant customers find the convenient engagement provided by the app to be most valuable. Hence, current accessing carries over to more accessing in the future. Since accessing the app translates more readily into purchase for distant customers, the net result of state dependence is to create more future sales by increasing long-term usage of the app.

Our focus has been on retailer apps as an engagement tool for distant and offline-only customers. The finding common to both groups is that app access translates more readily into purchase for these customers. This puts the onus on retailers to increase access. However, we find that access is difficult to stimulate through marketing. Promotions and offline advertising do stimulate access, but the effect, measured by elasticity, is small. Surprisingly, social media posts, whose copy is designed to stimulate app access is ineffective. We do not have the detailed data to discern why these social media posts are unsuccessful, a fertile area for future research.

While our core contribution is investigating the differential effectiveness of retailer apps for distant/near customers and offline-only/online customers, we contribute in two other ways. First, we model the process by which customers access retail apps and how this translates into purchase. For example, we show that state dependence and wear-out play important roles in this process. Second, by virtue of our finding that the app is more effective with offline-only than online shoppers, our results suggest that the value-add of retailer apps is as a new channel, more so than as an embellishment to directly visiting the retailer's website.

7.2. Managerial implications

Kannan and Li (2017) call for research on the impact of apps, and ask "as firms introduce mobile apps, what impact would they have on increasing customer equity and firm value?" Our work aspires to heed this call. Our core message is that app usage

Table 7
Summary of results: testing the propositions.

Proposition	Confirmed?	Conclusion
P1: Proposition 1: Distant customers exhibit		
a) less wear-out	No	Distant customers exhibit (a) similar wear-out, (b) more state dependence (Table 3, $\overline{\beta}_{1,1} = 0.045$, $p < .05$), and (c) a stronger translation of app access to purchase (Table 4, $\overline{\delta}_{1,1} = 0.020$, $p < .05$), compared to near customers, all else equal.
b) more state dependence	Yes	
c) higher translation of app access to purchase, compared to near customers, all else equal.	Yes	
P2: Proposition 2: Offline-only customers exhibit		
a) less wear-out	No	Offline-only customers exhibit (a) similar wear-out, (b) similar state dependence, and (c) a stronger translation of app access to purchase (Table 4, $\overline{\delta}_{1,2} = 0.016$, $p < .05$), compared to online customers, all else equal.
b) more state dependence	No	
c) higher translation of app access to purchase, compared to online customers, all else equal.	Yes	

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matters, and matters more for distant and offline-only customers by more effectively translating access into purchase. This suggests distance and channel usage are key segmentation variables for retailers targeting their app. For distant customers, the value proposition in consumer language might be "a convenient way to stay in touch". Every aspect of the app should be made as easy as possible – from finding products and promotions to comparing products and ultimately, to purchasing. For offline-only customers, the value proposition might be, "add the benefits of online shopping to your in-store shopping". Strategically, the retailer is providing superior digital engagement to complement offline-only customers' presumably high physical engagement.

Our results suggest that if distant and offline-only customers access the app, they will increase their purchase rate. This question of how to increase app usage has become more important as many firms are moving away from mobile app downloads as a key metric (Localytics, 2018). Localytics (2018) suggests numerous ways to increase app usage. They suggest simple features, including push notifications, individualization, and reminders sent through email and advertisements. When consumers on-board the app, it can be helpful to explain the value proposition of the app and how to use it. For example, the mobile app for Hootsuite, a social media management platform, starts off by showing their core value proposition before showing what the app can accomplish. Social networks Pinterest and Snapchat mobile apps both have unique interfaces, so they start with tutorials walking the user through how to share a pin and snap a photo, respectively. In terms of push notifications, being specific about their use is thought to lead to higher levels of opt-in behavior by consumers. For example, Yahoo's Weather app tells users exactly what time of day they will receive a notification about the weather. Our results resonate most closely with this final suggestion. Notably, our findings are that promotion, offline advertising and some app design (via upgrades) enhance mobile access for this retailer.

7.3. Limitations and future research

We investigate consumers who have downloaded the retailer's app. Focusing solely on this group allows us to detail how accessing the app affects purchase behavior, but as a result we cannot comment on how methods of acquiring app users determine app usage habits. Further work is needed on how to manage the adoption process.

We derive strong evidence that app access translates into purchase. However, as stated above, further research is needed, ideally in a field setting, to investigate "how to get the ball rolling", that is, how to increase access rates.

We study only a single mobile app. Future research should look at different apps. This might generate insight on which specific app designs (Kim et al., 2013; Zhao & Balagué, 2015) and other factors increase access and the impact of access on purchase. Next, our distance variable is somewhat rudimentary (0/1), and a more continuous measure of physical distance or traveling distance may enhance the precision of the findings. In addition, a more subtle operationalization of prior customer channel usage may provide further insights.

This research also presents results that, at first glance, appears to contrast with a recent working paper by Gu and Kannan (2018) which finds that mobile app adoption has a significantly negative impact on long term consumer spending. That is, while our study investigates the *usage* of a mobile app, Gu and Kannan (2018) study the *adoption* of a mobile app. While our study does not match adopters to non-adopters, our data does demonstrate that a substantial number of app users have decreasing sales over time. Nonetheless, further work which investigates if there is a relationship between mobile app usage by type of mobile adopter may be very interesting.

Finally, we do not observe the non-transactional aspects of engagement directly, e.g., how extensively the customer considers online user reviews. We assume for example that the offline-only shopper is less digitally engaged than the online shopper, and this seems reasonable given we *know* the online shopper has online activity. But more detailed measurement of engagement would be an important addition to our work.

Despite these limitations, we hope this paper will become a stepping stone in gathering an understanding on how consumers can be engaged through apps in an increasingly online-oriented world. We hope that future research will refine and extend this understanding.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijresmar.2019.03.003.

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