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# Shopper-Facing Retail Technology: A Retailer Adoption Decision Framework Incorporating Shopper Attitudes and Privacy Concerns

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**Abstract**

Continual innovation and new technology are critical in helping retailers' create a sustainable competitive advantage. In particular, shopper-facing technology plays an important role in increasing revenues and decreasing costs. In this article, we briefly discuss some of the salient retail technologies over the recent past as well as technologies that are only beginning to gain traction. Additionally, we present a shopper-centric decision calculus that retailers can use when considering a new shopper-facing technology. We argue that new technologies provide value by either increasing revenue through (a) attracting new shoppers, (b) increasing share of volume from existing shoppers, or (c) extracting greater consumer surplus, or decreasing costs through offloading labor to shoppers. Importantly, our framework incorporates shoppers by considering their perceptions of the new technology and their resulting behavioral reactions. Specifically, we argue that shoppers update their perceptions of fairness, value, satisfaction, trust, commitment, and attitudinal loyalty and evaluate the potential intrusiveness of the technology on their personal privacy. These perceptions then mediate the effect of the technology on shopper behavioral reactions such as retail patronage intentions and WOM communication. We present preliminary support for our framework by examining consumers' perceptions of several new retail technologies, as well as their behavioral intentions. The findings support our thesis that shopper perceptions of the retailer are affected by new shopper-facing technologies and that these reactions mediate behavioral intentions, which in turn drives the ROI of the new technology.


*Keywords:* Retail technology; Shopper privacy concerns; Proximity marketing; Self-scanning; iBeacons; Self-checkout

## Introduction

Retail technology capabilities have never been greater; retailers are faced with an increasing array of potential technologies that is expanding in its complexity and cost. Overall spending on retail IT was projected to exceed $190 billion worldwide in 2015 (Wilson 2014). Retailers are faced with a dizzying array of technologies and terminology, including iBeacons, mobile POS, Near Field Communications, and the Internet of Things. Retailers are understandably overwhelmed by the options and may adopt technologies without a clear picture of both how they fit into their strategy and, potentially more important, how shoppers will react.

When considering adoption of a new shopper-facing technology, more sophisticated retailers' decision calculus includes financial factors such as ROI, payback period, net present value, internal rate of return, and impact on profits. Projects that generate a sufficiently high ROI are then adopted and implemented. However, critical assumptions regarding the reaction of shoppers to the new technology are embedded in such calculations. These assumptions can either be explicit in terms of shopper metrics such as basket size and conversion or are simply implicitly assumed to be positive.

In this article, we argue that retailers' decision calculus for evaluating the adoption of shopper-facing technology needs to be expanded beyond what the technology **can** potentially deliver to consider shopper reactions and assess what the technology **will** deliver. Managers are often excited by their own side of the value equation, forgetting that shoppers may not share their enthusiasm. While the hope for positive effects from retail technology in terms of increased basket size, share of wallet, and

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profit are the motivating forces underlying the adoption of new technology, there are many examples of unexpected negative outcomes. For example, the recent data breaches at major retailers have increased shopper wariness of technology. Over 70 million households had at least some of their personal information stolen in the 2013 data breach at Target, including credit card information for 40 million households. Target also was embarrassed by a report in the *New York Times* that its data mining efforts used to target shoppers had led to a father discovering that his teenage daughter was pregnant (Duhigg 2012). Unfortunately, Target is not an isolated case. Other major retailers have suffered data breaches as well, including Home Depot in 2013 (56 million credit card accounts) and Nieman Marcus in 2013 (1 million credit card accounts).

On top of the costs of replacing shoppers' credit cards and the effect on the firm's stock price, a recent survey by CNBC suggests that such instances result in a shopper backlash fueled by lost trust (Conradt 2014). Specifically, they find that almost 70% of respondents correctly identified companies that had been breached and fifteen percent reported that they stopped shopping at breached retailers. Further, 30% reported planning to pay by cash in the future when shopping at a breached retailer instead of via credit or debit card—and spending tends to be lower when paying with cash (e.g., Inman and Winer 1998).

In the face of such potential consequences, how should a retailer evaluate a new shopper-facing technology and decide whether to adopt it? Surprisingly, an interested retailer will find little guidance in the academic literature. While the literature has examined the effect of specific technologies such as self-service technologies (e.g., Meuter et al. 2000, 2005), payment systems (e.g., Giebelhausen et al. 2014), and mobile coupons (e.g., Hui et al. 2013), there is currently no framework to which a retailer can avail to guide consideration of a new shopper-facing technology. That is the focus of this article.

We begin by briefly reviewing some of the major technological innovations in retail during the past 50 years. We then present our equity theory-based framework that examines retail technologies through the lens of its potential positive and negative consequences for the retailer versus its potential positive and negative consequences for shoppers. We close with a series of examples and a survey of shopper reactions to potential retail technologies that are looming on the horizon.

## A Brief Overview Of Retail Technology: Past, Present, And Future

Many major technological innovations have revolutionized retailing over the past several decades. In this section, we describe some of them and then discuss more recent innovations as well as technologies that are beginning to be broadly introduced by retailers. We do not claim to capture every innovation, but rather focus on some of the most disruptive retail technologies that we identified from conversations with several industry experts.

### *Past Retail Technology Highlights*

#### *Barcode Scanning*

Arguably the most important retail technology innovation in the twentieth century was the adoption of the UPC barcode scanning after developments of the 1960s such as inexpensive lasers and semiconductors finally made scanners simple and cost effective (Seideman 1993). In 1974 at a Marsh supermarket in Troy, Ohio, the first retail product was sold via a scanner—a pack of chewing gum. Once 85% of all products carried UPC codes a few years later, adoption of barcode scanners took off. For example, less than one percent of grocery stores nationwide had scanners in 1978, but by 1981 the figure was ten percent and a third of U.S. grocery stores were using scanners by 1984. Today, virtually every retailer is equipped with a barcode scanner.

The capability to scan items using a standardized code provided retailers with real-time transaction data and enabled them to identify fast-moving items. Retailers could also couple these data with information on shelf space allocation to create metrics to assess product-level ROI. Importantly, transaction data were collected more accurately and objectively and could be combined with data on causal factors such as price, feature advertising, and display to estimate the drivers of sales. The availability of scanner data also spurred a sizable body of research on quantitative models of consumer buying behavior (e.g., Guadagni and Little 1983). Today, scanner data are a mainstay of performance tracking and strategic decision making for retailers and CPG firms alike. In fact, it would not be an exaggeration to say that the advent of scanning technology made possible much of the retail technology innovation that has followed.

#### *Videocart*

While much is made today of location-based marketing, this is not a new concept. In fact, Malec and Moser (1994) filed a patent in 1988 for an "Intelligent Shopping Cart System Having Cart Position Determining and Service Queue Position Securing Capability." The abstract describes the system as a "shopping cart display system that includes a cart mounted display that is responsive to unique trigger signals provided by respective transmitters associated with respective fixed locations. When the display receives a unique trigger signal, it displays advertising associated with the respective location." For example, the system would know when the shopper is in the dairy section and could show an ad for Dannon yogurt. The ads would be funded by the CPG firms. A sketch of the cart from the patent is shown in Fig. 1.

Moser formed Videocart, Inc. which was touted by the New York Times (Henriques 1991) as, "Videocart Inc., whose computer-equipped shopping cart provides point-of-purchase advertising as the shopper moves through the store." The first author recalls using a Videocart at a Vons supermarket in Hermosa Beach in 1991. At Videocart's peak in 1992, 46,000 shopping carts were fitted with the displays in retailers such as Schnucks in St. Louis and Dominicks in Chicago. However, in 1993 Videocart filed for bankruptcy.

Several reasons underlie the failure of Videocart. First, most of the pop-up ads were reminder ads and did not offer a financial

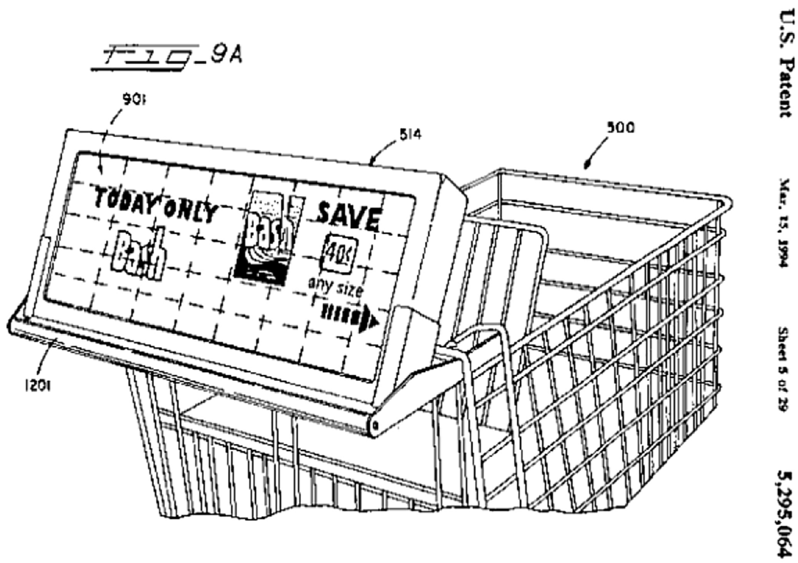


Fig. 1. Videocart sketch from original patent 5,295,064.

incentive for shoppers, making the effect on incremental sales difficult to measure. Second, shoppers did not like the screen location mounted on the handle, which blocked a view of the cart and took up a large part of the cart's seat, which many shoppers used to place valuables, fragile items, or a small child. Finally, retailers had difficulty keeping the batteries on the device charged, so oftentimes shoppers were pushing a nonfunctioning cart. Additionally, the costs and installation of the on-cart display units and the in-store infrared system were prohibitive.

*In-Store Coupon Dispensers*

In 1992, Patent 5,083,765 was awarded to George Kringel for a device described as a "stand-alone dispenser including an integral electrical power supply provided for reliably dispensing individual sheets, such as coupons, from a stack" (Kringel 1992). The assignee was ActMedia, which rolled them out in retailers across the country. Stores would install the coupon dispensers next to the product for which the coupon was offered. A limited number of dispensers were installed in each store because CPG firms that paid to have the dispenser for their product would be given category exclusivity. By 1996, ActMedia had annual sales of approximately $500 M and was in 40,000 supermarkets, drugstores, and mass merchandisers. News America entered the at-shelf couponing business in 1996 and acquired the parent company of ActMedia in 1997. News America subsequently renamed the dispenser the SmartSource Coupon Machine.

In 2007, a patent was granted for a "process for distributing product entitlements to members of a retail store's frequent shopper program" (Muldoon 2007). This patent describes a process for distributing coupons at a retailer to members of the retailer's frequent shopper program (FSP). The process focuses on comparing the shoppers' purchase history to available coupons. The shopper enters their FSP number into the dispenser in the store, which triggers coupons that fit the shopper's purchase history. The coupons are then redeemed at checkout. Today, CVS is an example of a retailer that uses in-store coupon dispensers to offer loyalty card members coupons based on their previous purchase history.

*Kiosks*

A kiosk consists of a touchscreen, a computer, and perhaps a printer and credit card reader—all enclosed in a secure cabinet. Kiosks can deliver information or they can promote and sell products and services. Most kiosks are located in public places, such as stores, airports, malls, and hotel and corporate lobbies. The landmark implementation of kiosks is credited to Florshiem Shoes, which installed them in 1985 in over 600 locations. The kiosks provided images and video promotion for shoppers who wished to purchase shoes that were unavailable in the particular store. The purchase could be paid for at the kiosk and the transaction was then transmitted to Florsheim for delivery to either the shopper's home or to the store.

While the Florsheim system became the benchmark for innovative self-service shopping technology, it is only in the past few years that the kiosk market has taken off. Kiosks have now spread across a wide array of venues, such as airports, hotels, banks, grocery stores, and clothing stores. Kiosks are used to dispense money (ATMs), boarding passes, tickets for movies, trains, and theaters, and DVDs. The firm Outerwall alone operates over 40,000 Redbox DVD dispensing kiosks and over 20,000 self-service Coinstar coin-counting kiosks throughout the U.S. (Outerwall Company 2016). Total revenue for Outerwall was $2.2 B in 2015.

*Walmart Smart Network*

Walmart pioneered the idea of shopper media through its Walmart Smart Network. The goal of the Walmart Smart Network was to increase category sales by communicating to shoppers at or near the point of purchase. The sales pitch seemed compelling: in a very fragmented media landscape, advertisers could reach almost 8 million Walmart shoppers each week via 27,000 screens across 2,700 stores. Video monitors would be positioned throughout the store in strategic locations to communicate information to shoppers about topics such as new products and limited time offers. The Walmart TV network was rolled out in 1998 and consisted of CRT monitors mounted high above the retail floor showing ads. The Walmart TV Network provided another source of revenue for Walmart, as vendors could fund the ads from their advertising budget rather than from their trade promotion budget. Across its stores in the U.S., Walmart TV was projected to capture 130 million viewers monthly (Hays 2005).

The ads initially included audio, which inadvertently led to employee fatigue, shopper irritation, and lower ad effectiveness. The Walmart Smart Network replaced the aging Walmart TV network and debuted in 2008. It was touted as a "next generation retail media network that is supported by a flexible, open enterprise platform powered by Internet Protocol Television (IPTV)—technology that will allow the retailer to monitor and control more than 27,000 screens in more than 2,700 stores across the country" (Sharma 2008). The new Walmart Smart Network deploys response measurement and message optimization technologies that enable delivery of relevant content to shoppers and that can be varied by store, by screen, and by time-of-day.

## *Present Day Retail Technology—Already Here and On the Horizon*

### *Mobile Apps*

It seems that almost every retailer these days has a mobile app. However, the capabilities of these apps vary quite a bit across retailers. Some have relatively limited options such as a store finder, ability to download coupons, or view the weekly circular electronically, while others offer an omnichannel experience. For example, Target's app offers shoppers the ability to scan products to see if there are special offers, receive mobile coupons as they move through the store, download a store map to find products within each Target store, and buy items online through the app.

A recent study of mobile app users by mobile consulting firm Applause sifted through user reviews for retailer mobile apps (Gray 2015). Among apps that received the highest app quality scores, the common themes were the capability to see deals, easily switch between PC and mobile, and receive in-store alerts. A recent study performed by Forrester (2015) reinforced the sense that U.S. consumers are using smartphones to shop in an anytime, anywhere fashion and retailers are striving to engage with shoppers at these critical touch points. However, retailers are struggling with convincing shoppers that they need more retailer apps as consumers strive to pare back on the apps they have on their phone. Consumers would prefer more integration in a retailing app; that is, they would like a single app via which they can search across retailers and buy whenever the need arises.

### *Self Scanning*

Self-scanning checkout, also called "self-checkout," is an automated process that enables shoppers to scan, bag, and pay for their purchases without the need for a cashier. In most stores, a self-scanning checkout lane looks like a traditional checkout lane except that the shopper interacts with a computer's user interface instead of a store employee. Once the shopper begins the checkout process, the self-scan interface guides the shopper through the process of scanning each item and where to place it after it has been scanned. The patent (see Fig. 2) for an 'automated point-of-sale machine' was awarded in 1992 (Schneider 1992) and the first self-checkout system was installed in 1992 by Price Chopper Supermarkets.

When the shopper scans an item, the item's barcode provides the computer with the information it needs to determine what item is being scanned, as well as the item's weight and current price. To mitigate pilfering, when the computer's animated voice directs the shopper to place the scanned item in a shopping bag, the item is also being placed on a security scale that compares the weight against the last scanned item. This prevents shoppers from scanning one item and placing two into the bag. Typically, there is a cashier supervisor for every four to six self-scanning stations. In a global study (NCR 2014) of 2,800 shoppers conducted across nine countries, 90% of respondents reported that they use self-checkout. Respondents report that they like the convenience of self-checkout, find it simple to use, and think it is faster than a cashier assisted lane.

### *QueVision*

Kroger has embraced the use of technology to reduce shopper wait time at checkout, rolling out a new system called QueVision across its 2,400 grocery stores in 2010. The system couples infrared sensors that count shoppers with analytics based on "Little's Law" (Little 1961) to quickly open more checkout lanes when shopper waiting time has exceeded a preset threshold. Little's Law from queueing theory, represented in the simple equation $\mathbf{L} = \boldsymbol{\lambda} * \mathbf{w}$, asserts that **L**, the average number of shoppers in a queueing system, is equal to $\boldsymbol{\lambda}$, the rate at which shoppers arrive and enter the system, times **w**, the average trip time of a shopper.

QueVision reportedly has reduced the average shopper wait time at checkout from more than four minutes to less than 30 s (McLaughlin 2014). Since over 7 million shoppers visit Kroger each day, this reduction in wait time equates to over 400,000 h of saved time each day. Shopper satisfaction with the speed of checkout has increased by 42% and revenue has increased as well, which Kroger attributes to shoppers allocating less time to waiting in line and more time to shopping. QueVision has also helped Kroger free up parking space at urban stores where parking is limited (Coolidge 2013).

There are several other companies that offer similar sensors to count store traffic. For example, ShopperTrak (Chicago) and Traf-Sys (Pittsburgh) claim a large installed base of counters. The traffic counts are combined with POS data to help retailers track conversion rates (the proportion of people entering the store that actually make a purchase), assess the effectiveness of out-of-store advertising on traffic, and optimize their staffing to ensure coverage during peak times.

### *Smart Shelves*

Retailers have recently been experimenting with "smart shelves" that offer the promise to reduce out-of-stocks through

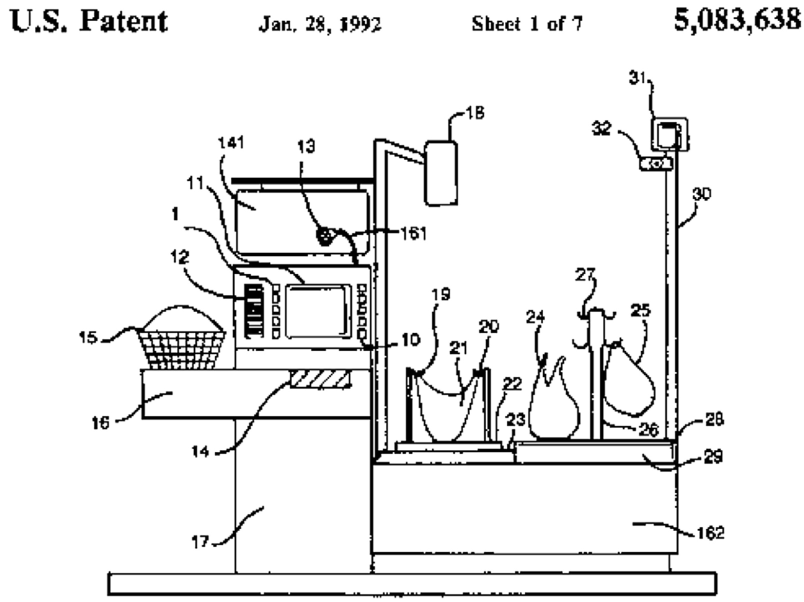


Fig. 2. Self-checkout sketch from original patent 5,083,638.

weight sensors on the shelves. A weight-sensitive mat is placed on the shelf and a notification is sent to store personnel when the last item is removed. If reserve stock is on hand, this system mitigates lost sales and shopper irritation from out-of-stocks.

The shelves also include beacon-activated mobile advertising. A beacon works via Bluetooth technology and beacon communications consist of small packets of data. Beacons transmit packets of data at set intervals to be accepted by shoppers' smartphones, where they can be used to trigger marketing messages such as push messages and app actions. When one of the apps receives a beacon broadcast, it communicates the data to its server, which triggers an action such as a promotion, a targeted advertisement, or even a helpful reminder (e.g., Got Milk?). The premise is that beacons will help increase the connection between retailers and shoppers and improve the shopping experience because the proximity-based communication and at-shelf advertising allow retailers to ensure that shoppers only receive relevant information and discounts.

Finally, many smart shelf systems incorporate digital price tags, which allow retailers to change prices remotely. The potential benefits of digital price tags are twofold. First, the potential labor savings are substantial, since many retailers sell thousands of SKUs and changing paper price tags requires many hours of employee time. At present, new pricing is sent to stores on a weekly basis, with about twenty percent of products needing to be updated per week. This is typically done manually; store associates go through the store and replace the price tags on the affected items.

Second, digital price tags allow retailers to change prices dynamically. For example, a grocery store could slowly lower the price on its baked goods throughout the day in order to avoid having excess inventory at the end of the day. Leveraging this capability requires analytics that enable the retailer to estimate demand on an hourly basis, coupled with real-time inventory information. Shoppers and retailers will both benefit from such a use; shoppers who shop later in the day would pay less and the retailer will avoid spoilage.

However, digital price tags also offer the potential for retailers to engage in "surge pricing," raising prices to extract greater surplus from shoppers with a higher willingness to pay. Using POS data, a retailer could estimate the variation in shopper price elasticity for product categories across time of year, day of week, and even time of day and "optimize" the price to maximize revenues. For example, a retailer could increase the price of its prepared foods at dinner time when shoppers are in a hurry and are willing to pay a higher price for the convenience of purchasing a heat-and-serve meal solution. Clearly, such an opportunity will be quite attractive to retailers, probably less so to those shoppers who have to pay a higher price.

*Gravity Feed Shelving Systems*

Gravity feed shelving systems such as that introduced by Campbell Soup in 2002 has revolutionized the canned soup category. Campbell's gravity feed system is installed in over 20,000 stores. A gravity feed shelving system consists of a sloped shelf for supporting merchandise and a front wall that hold the merchandise in place until a shopper takes the front product. When the front item is removed, gravity pushes the remaining merchandise down the sloped shelf to the front. This system automatically maintains the appearance of the shelf, requires less attention from store personnel and lowers labor costs. Shoppers find such displays easier to navigate and more pleasant to shop. According to McCormick and Company, the gravity feed fixtures for its spices increased sales in installed retailers by over five percent and cut labor costs in half (Karolefski 2008).

*Personalized Promotions/Pricing*

Pioneered by dunnhumby at Tesco and Kroger, retailers are using datamining of their loyalty card data with the help of consulting firms such as EYC, Catalina, and Aimia to identify their best customers and develop offers that increase retention. A focal objective in this domain is "relevance"—offering promotions on products that are of interest to the shopper and address their specific needs. For example, Catalina Marketing provides personalized coupons for retailers and brands by tracking the behavior of more than 230 million U.S. shoppers monthly. Kroger sends out over 12 million mailers to their best customers each quarter. Catalina Marketing claims that every $1 in promotional offers generates $8 in extra sales (Kharif 2013).

Taking the idea of personalized promotions one step further, retailers are now experimenting with "proximity marketing" during the shopping trip. Coupling smart phone technology and loyalty card data, retailers are attempting to reach shoppers with personalized offers in real time. The platform collects continuous feedback during each shopper's trip and uses sensor readings from shoppers' smartphones to calculate position and movement. This is coupled with loyalty data to deliver relevant messages and offers at key moments. Messages can be triggered based on a shopper's location, movement, and dwell time. For example, a shopper dwelling in the ice-cream section could be sent an ice-cream coupon. Alternatively, the platform can provide coupons that urge the shopper to visit more of the store to spur unplanned purchases (Hui et al. 2013). Finally, shopper movement data can be used to gauge shopper momentum in the store to prevent shoppers having to backtrack.

*Scan and Go*

Several retailers have begun to test or introduce technology that allows shoppers to use their smartphone to scan items as they put them in their basket. Shoppers can then use the scanned data via the retailer's app to pay without having to scan the items again at the checkout line. The technology offers the potential for improved shopper satisfaction from the convenience and reduced wait time, along with labor savings to the retailer (analogous to self-checkout discussed above). However, retailers are still struggling with leveraging this value. Walmart tested this technology in 200 of its stores in 2013–2014 and found that shoppers had difficulty in learning how to use the app. The perceived complexity of using an app may explain the result that 41% of consumers prefer the retailer to provide them a device to use while shopping (CFI Group 2014).

*In-Store CRM*

In the film *Minority Report*, Tom Cruise's character is bombarded by ads as he walks through a mall. In the film, shoppers are recognized by a retinal scan of their eyes, which is then used to serve up personalized content. The ads mention him by name, implying that they are targeted specifically to him. While this type of technology has been commonplace for online retailers for years (e.g., Amazon customizes the products that people see based on their previous purchases or items they have put in their cart), this rarely happens in the physical world. When shoppers enter a store, the company does not know their identity.

This, too, is beginning to change. Retailers are beginning to experiment with facial recognition software that will help them identify shoppers unobtrusively. Furthermore, companies like RetailNext are able to recognize customers based on their smartphones and track key metrics such as shopping path and dwell time. Pushing the envelope further, Realeyes, which analyzes facial cues to monitor response to video advertising, can potentially track shoppers' emotions as they shop the store. Powered Analytics, a start-up in Pittsburgh that was recently acquired by Target, focuses on personalizing in-store shopping through mobile technology, location data, and predictive analytics. The goal is to bring an online shopping experience into physical stores. Finally, in 2013, Nordstrom began testing technology that allowed it to track customers' movements by following the Wi-Fi signals from their smartphones. However, when Nordstrom posted a sign telling shoppers that it was tracking their behavior, shopper reaction was so negative that Nordstrom ended the experiment.

## Shopper-Facing Retail Technology Adoption Decision Framework

When considering adoption of new shopper-facing technology, sophisticated retailers consider the profit implications. That is, the retailer evaluates whether the benefits of the technology will outweigh the costs of purchase, installation, and maintenance. These benefits tend to result from the technology increasing revenues, decreasing costs, or both. As shown in Fig. 3, revenue increases and cost decreases can derive from various sources. Revenues can be increased by extracting greater consumer surplus (e.g., charging higher prices to shoppers who are willing to pay more), increasing the amount purchased at the retailer by current shoppers, attracting new shoppers to the retailer, and increasing payments from suppliers, while costs can be decreased by offloading labor to shoppers (e.g., self-scan) or by automating processes (e.g., digital shelves). Each of these is discussed in more detail below.

*Extracting Surplus*

Consumer surplus is the net gain that a buyer receives from purchasing a good or service. Specifically, it is the difference between what the buyer would have been willing to pay and the actual price. In terms of the demand curve, it is the area below the demand curve, above the price, and left of the quantity bought (set at the market clearing price where supply equals demand). For example, the buyer might be willing to purchase a certain brand of coffee maker for $50. If the retailer's price is $39, then the buyer enjoys a consumer surplus of $11.

It is tempting for retailers to seek ways to extract this surplus by charging differential prices based on shoppers' differences in willingness to pay, analogous to revenue management in the airline industry. Technology offers this promise. For example, if the retailer can identify the shopper via NFC or facial recognition technology, the retailer can offer mobile coupons that are tailored to the shopper's price sensitivity. Alternatively, digital shelves provide the opportunity for analytics to estimate how shoppers' price sensitivity varies throughout the day and raise price at times of day or days of the week when price sensitivity for the product category is lower. For example, analysis might reveal that prices for prepared food could be dynamically increased

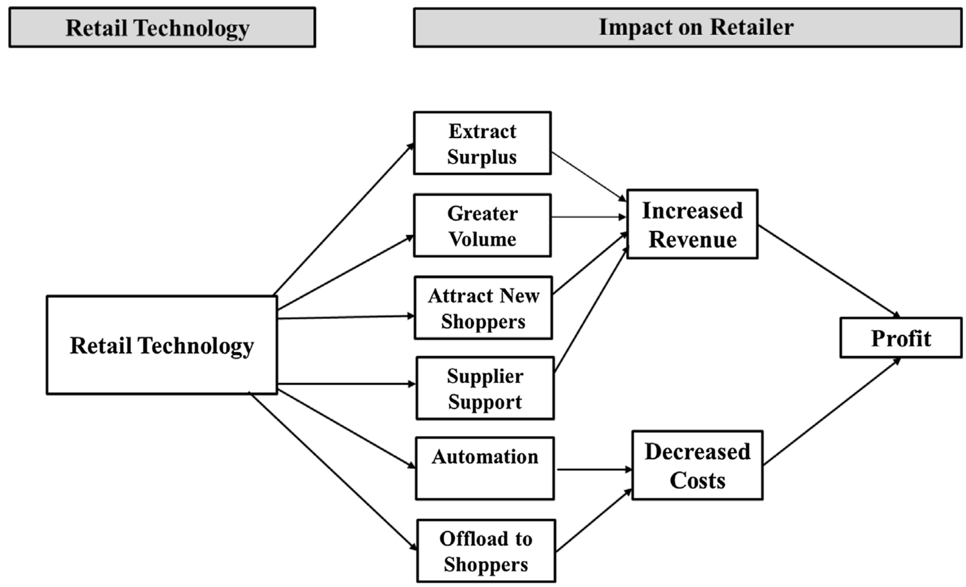


Fig. 3. Current decision calculus.

at lunchtime, or RFID monitoring of stock levels might lead to retailers increasing price as stock levels decline in order to leverage scarcity effects.

*Increasing Quantity Purchased by Current Buyers*

Most shoppers satisfy their household requirements for goods across several retailers. That is, they engage in channel blurring in most product categories (e.g., Luchs, Inman, and Shankar 2016). A potential benefit of new technology is encouraging shoppers to (a) purchase a greater share of their requirements for any given category from that retailer, and (b) purchase categories from the focal retailer that they currently do not purchase at all from that retailer but from other retailers. This implies that retailers can profile their shoppers using geodemographic purchase patterns and compare the potential purchases against shoppers' loyalty card data to identify opportunities to increase share of wallet.

*Attracting New or Lapsed Buyers*

One of the largest potential sources of increased revenues is new buyers. These shoppers have yet to form an impression of the retailer or to establish buying habits. Unfortunately, this is arguably the most difficult opportunity to leverage, since retailers are presently unable to identify new buyers as they enter the store. However, lapsed buyers can potentially be targeted via e-mail with "we haven't seen you in a while" coupons or incentives to persuade them to return to the store.

*Increasing Payments from Suppliers*

As retail technologies improve retailers' ability to target shoppers more accurately, the value of this capability to suppliers increases. This allows retailers to extract more funds from suppliers who wish to have access to targeted buyers. For example, a retailer with scan and go technology that has a large shopper base will be potentially attractive to suppliers who wish to contact shoppers at the point of purchase and offer an incentive to purchase their brand.

Alternatively, a retailer with a shopping app that enables shoppers to use their purchase history to create a shopping list could offer suppliers the opportunity to bid for the right to have their brand listed earlier in the list of prior purchases. For example, Costco could add an option to its app or website where shoppers could access their shopping history in creating a shopping list. Suppliers such as Pepsi or Unilever could be offered the opportunity to bid for the option of having their products receive more prominent display such as being listed at the top of the list or in bold font. Suppliers could also bid for the option of being listed as a substitute for a competitor brand.

Some shopping apps now offer the utility to shoppers to create a shopping list. The shopper uses the list to guide her purchases, then this data can be linked to the shopper's loyalty account. This enables the retailer to assess which items tend to be planned in advance (i.e., was included on the shopping list) versus which items tend to be chosen at the point of purchase (unplanned purchases). Suppliers whose brands tend to be purchased on an unplanned basis are likely more susceptible to disruption by competitors' promotions than brands that are planned in advance. Thus, retailers can potentially offer suppliers the opportunity to utilize this information to send coupons to shoppers who tend to purchase items on an unplanned basis. Suppliers would be willing to pay a great amount for such a targeted opportunity.

*Offload Labor to Shoppers*

Retailers occasionally offload labor to shoppers which results in costs savings. Some readers will recall visiting Blockbuster

Video, where shoppers would select their videos then take them to the counter and check out. Today, shoppers can go to a RedBox at a local retailer and perform this transaction by themselves. Relatedly, they can decide to use the self-checkout lane at the local home improvement store. Innovations in scanning technology and vending technology have made it possible for retailers to remove retail staff from many activities and convert them into self-service activities where shoppers perform a greater portion of the work.

*Automation*

Another driver of cost savings for retailers is automation. As discussed earlier, digital price tags on smart shelves allow retailers to change prices remotely, resulting in tremendous costs savings as they reduce the enormous amount of employee time necessary to manually update prices on a weekly basis. Similarly, the use of gravity feed shelfing systems lowers labor costs because they automatically maintain the appearance of the shelf and thus require less attention from store personnel. Finally, suppliers are increasingly using prebuilt displays that contain products in display-ready format. The retailer only needs to open the box and put the entire unit on the retail floor. This greatly reduces the labor needed for set-up of conventional displays.

## An Equity Theory Perspective of Retail Technology Adoption

If the benefits of a new technology accrue to the retailer at shoppers' expense (e.g., higher prices), the ratio of shoppers' outcomes/inputs may decrease while the ratio of retailer's outcomes/inputs increases. In this case, shoppers may perceive the situation as unfair and react negatively by complaining or even switching to another retailer. This is the centerpiece of our proposed shopper-focused decision calculus for retailers considering the adoption of a new shopper-facing technology.

Adams (1963) describes perceived equity as a function of the comparison of the ratio of the actor's outcomes/inputs in an exchange relationship against those of a referent party. Inequity results when the actor's outcomes/inputs are not commensurate with those of the referent. Blau (1964) distinguishes between economic exchange relationships and social exchange relationships. Economic exchange relationships are shorter term, quid pro quo, and involve weaker interpersonal attachments. People engaged in an economic exchange relationship tend to expect more immediate payback and are less forgiving of inequities.

Molm (2003) extends Blau's (1964) framework, arguing that there are two forms of exchange relationships: negotiated and reciprocal. The most pertinent type of relationship in a retailer-shopper context is reciprocal exchange. Reciprocal exchange relationships are engaged in voluntarily by both parties without specific terms regarding what is to be exchanged or the timeframe of the exchange. These types of relationships tend to result from a successful series of interactions between two parties, such as between shoppers and a retailer. Consistent with Blau's arguments, Molm et al. have found that the dynamics of each type of relationship differ. Their research shows that reciprocal exchanges produce lower levels of power use and inequality (Molm, Peterson, and Takahashi 1999), stronger engendered trust and affective commitment among the parties involved (Molm, Takahashi, and Peterson 2000), and stronger perceptions of fairness (Molm, Takahashi, and Peterson 2003).

Incorporating customers' needs into the firm's decision is at the heart of customer relationship management (CRM). In fact, a major tenet of CRM is the consideration of customer intelligence across all customer-facing functions (Reinartz, Krafft, and Hoyer 2004). Relatedly, Morgan and Hunt (1994) argue that managing ongoing customer relationships is the essence of the marketing concept and that the maintenance of successful relationships requires commitment and trust. Kumar and Reinartz (2012) argue that understanding individual customer needs has become a key source of competitive advantage and that all marketing activities should center around the effect on the customer.

As shown in Fig. 4, our framework augments the standard decision calculus by adding a mediating effect of shopper perceptions and reactions to the new technology. That is, we argue that the benefits accrued from a new technology are largely dependent on how it is received by shoppers. If shopper perceptions toward a particular technology are negative, then the monetary benefit of that technology will be attenuated or even reversed.

More specifically, our framework predicts that a new technology will be assessed by shoppers in various respects and they may update the perception of their relationship with the retailer as a result of this assessment. This assessment and updating may lead to a behavioral reaction by shoppers. First, the shopper may decide to change their purchase behavior at the retailer, perhaps by buying more (or less) quantity in a given product category, buying categories at the retailer that they previously only purchased at another retailer, or switching away from the retailer to a competitor. Second, shoppers may engage in word of mouth by sharing their perceptions with other shoppers—perhaps through a shopper forum on the retailer's website. Below we describe in more detail the most salient potential shopper perceptions that might be affected by new technology and the shopper reactions that might result.

*Shoppers' Perceptions*

*Justice/Fairness Perceptions*

Justice (or fairness) perceptions (the two terms are often used interchangeably in the literature) play a key role for determining shoppers' utility from transactions with retailers, shoppers' behaviors, as well as the quality of retailer-shopper relationships (Anderson and Weitz 1989; Guo 2015; Oliver and Swan 1989). Perceived justice or fairness can be defined as a judgment of the extent to which people believe that there is equity in the exchange between themselves and another party (Maxham and Netemeyer 2003). Research distinguishes between three types of fairness which influence how shoppers evaluate their exchanges with retailers—procedural fairness (fairness of procedures and policies), distributive fairness (fairness of outcomes received), and interactional fairness (fairness of treatment) (Maxham and

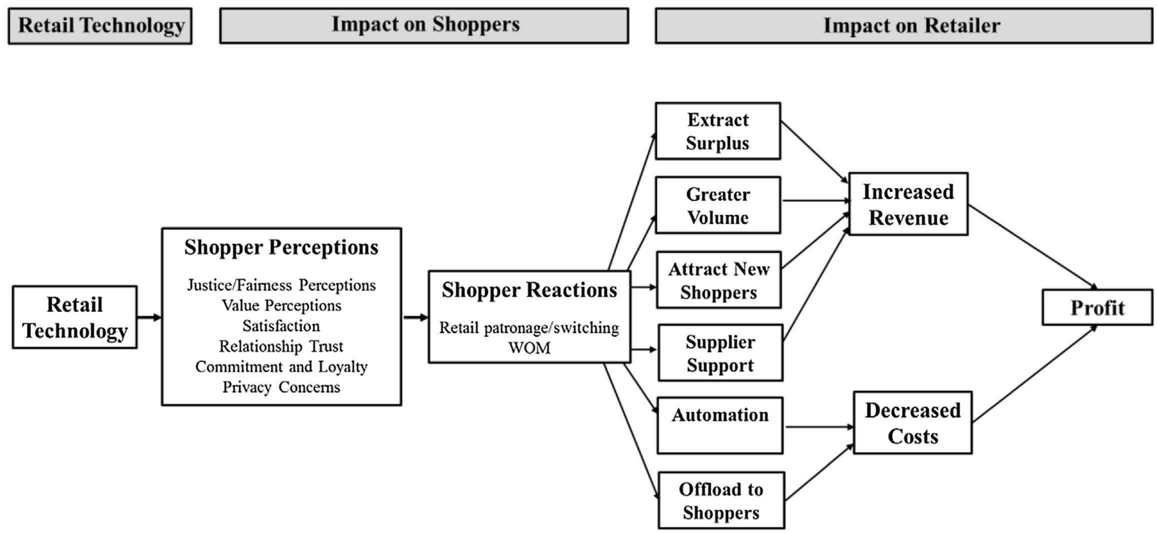


Fig. 4. Shopper-focused decision calculus.

Netemeyer 2003; Kumar, Scheer, and Steenkamp 1995; Tyler and Lind 1992). Perceptions of unfairness occur when shoppers perceive that their ratio of inputs to outcomes is inequitable in comparison to the retailer's ratio (Maxham and Netemeyer 2003).

One particular subtype of fairness that has garnered a lot of attention in the marketing literature during the last decade is price fairness. Campbell (2007) defines price (un)fairness as "a consumer's subjective sense of a price as right, just, or legitimate versus wrong, unjust, or illegitimate." Guo (2015) suggests that in market settings, shoppers compare their payoffs with the retailers' profits and are averse to prices which involve an inequitable ratio. Retailers need to pay attention to shoppers' price fairness perceptions because they play a key role for determining purchase intentions, willingness to pay, as well as retail patronage such that consumers are willing to punish firms they perceive to be unfair (Campbell 1999; Guo 2015).

Given the importance of fairness perceptions for determining shoppers' behavior in the marketplace, it is essential for retailers seeking to implement various retail technologies to assess how such endeavors might impact shoppers' fairness perceptions. While procedural fairness and interactional fairness might be less impacted by the implementation of shopper-facing technologies, perceptions of distributive fairness, and particularly price fairness, would be more likely to be affected by some retail technologies. For example, technologies that offload labor to shoppers such as self-checkout lanes might lead to increased distributive unfairness perceptions as they increase the shopper's ratio or inputs to outcomes in the retailer-shopper exchange. In particular, smart shelves which allow retailers to raise prices at times of day or days of the week when price sensitivity is low and thus extract consumer surplus, might lead to perceived price unfairness and be aversive to shoppers.

On the other hand, retail technologies such as Scan and Go that decrease shoppers' inputs in the exchange with the retailer (by decreasing time commitments) might lead to increased distributive fairness perceptions. However, it is important for retailers to understand that fairness perceptions are biased by the buyer's self-interest (Oliver and Swan 1989; Xia, Monroe, and Kent 2004) such that they are less severe when the inequity is to the buyer's advantage than when the inequity is to the buyer's disadvantage (Ordóñez, Connolly, and Coughlan 2000). Therefore, shopper-facing technologies that increases (vs. decrease) the ratio of inputs to outcomes for shoppers might be more likely to influence their fairness perceptions and their behavior with respect to the focal retailer; thus retailers need to be attuned to shoppers' reactions to such technologies.

*Value Perceptions*

Consumers' value perceptions are considered another important determinant of their shopping behaviors (e.g., Zeithaml 1988). Zeithaml (1988) defines perceived value as "the consumer's overall assessment of the utility of a product based on perceptions of what is received and what is given (p. 14)." In the context of retailer-shopper relationships, perceived value would be defined as the shoppers' assessment of the overall utility of an exchange with a retailer based on perceptions of what is received and given (Dodds, Monroe, and Grewal 1991). In other words, value perceptions result from the difference between the benefits received by the shoppers and the sacrifices they need to make in the exchange with the retailer. For instance, some of the benefits that shoppers gain from their exchange with retailers include but are not limited to quality products, personalized promotions, just-in-time promotions, and a convenient shopping environment. On the other side of the equation, the sacrifices that shoppers make include both monetary sacrifices (i.e., the price they pay) and non-monetary sacrifices such as the time and effort spent to acquire products (Cronin, Brady, and Hult 2000; Dodds, Monroe, and Grewal 1991). Consequently, in order to maximize shoppers' perceived value, retailers should either decrease the monetary and non-monetary sacrifices or increase the benefits offered (Dodds, Monroe, and Grewal 1991; Zeithaml 1988).

Given the generally favorable impacts of positive shoppers' value perceptions on retailers' performance (e.g., Wakefield and

Barnes 1996), a retailer considering a new retail technology should pay careful attention to how this action might affect shoppers' value perceptions. For example, as discussed earlier, the reasons why Videocart failed were (1) the location of the screen on the handle, which took up a large part of the cart's seat, which many shoppers use for different purposes; and (2) dead device batteries which retailers forgot to charge and which made the cart non-functioning. In other words, the Videocart technology both decreased shoppers' benefits and increased their costs (as they had to push a heavier, non-functioning cart), resulting in lower value perceptions.

As far as the newer retailer technologies are concerned, technologies such as QueVision, which helps retailers quickly open more check-out lanes when a predetermined waiting time threshold for the existing lanes has been exceeded, should decrease shoppers' non-monetary sacrifices (i.e., time) in their exchange with the retailer, resulting in higher value perceptions. In addition, technologies that allow retailers to offer their shoppers just-in-time, personalized promotions should have a positive impact on the benefits side of the shoppers' value equation, leading again to higher perceived value. In contrast, technologies that enable self-service activities might lead to increased cost perceptions since they offload labor to shoppers; if such technologies do not bring about a simultaneous increase in benefits (such as more convenience, lower wait time, etc.), they might decrease shoppers' perceived value.

*Satisfaction*

Customer satisfaction has well-documented benefits for firms. Prior research shows that satisfaction determines choice and purchase behavior (e.g., Rust and Zahorik 1993) and has been linked to market share (Anderson, Fornell, and Lehmann 1994), shareholder value (Anderson, Fornell, and Mazvancheryl 2004), profitability (Mittal et al. 2005), and stock price (Fornell et al. 2006).

Given the documented benefits of customer satisfaction for customer retention and loyalty and for a firm's performance, we argue that retailers should assess how the various technological innovations they are considering might impact their shoppers' satisfaction. For instance, if a retailer discovers that a particular retail technology has a significant negative impact on customer satisfaction for various reasons such as diminished value perceptions or perceived unfairness, this might be an important argument against the adoption of the technology.

*Relationship Trust*

Trust can be defined as one party having confidence in their exchange partner's integrity and reliability (Morgan and Hunt 1994). In the context of shopper-retailer relationships, shoppers' trust would represent an overall belief that the retailer will generally take actions that will result in positive outcomes for the shopper and will refrain from taking actions that might have negative consequences for the shopper (Anderson and Narus 1990). Trust is associated with beliefs that the exchange partner is fair, responsible, helpful, benevolent, honest, consistent, and competent (Altman and Taylor 1973). According to Morgan and Hunt (1994), there are three antecedents of developing trust in firm-customer relationships: (1) shared values, which represent the extent to which both the retailer and shoppers agree on what behaviors, procedures and policies are important, appropriate, and correct; (2) communication, which refers broadly to the sharing of important information between the relationship partners in a timely manner (Anderson and Narus 1990); and (3) opportunistic behavior, or a deceit-oriented, self-interested behavior which violates norms of behavior (Williamson 1975).

Building trust is a key component of building strong, profitable customer relationships (e.g., Reichheld and Schefter 2000) and as such, retailers need to pay attention to how new technologies might impact shoppers' trust. In the context of our retail technology adoption decision calculus, it would be important for retailers to consider if different retail technological advancements might be perceived as opportunistic behaviors or actions that might diminish shared values perceptions, both of which have a negative impact on trust (Morgan and Hunt 1994). For example, smart shelves that allow retailers to estimate price sensitivity variations throughout times of the day and days of the week and adjust prices to accommodate these changes might be perceived by shoppers as opportunistic behaviors in which the retailer acts in a purely self-interested manner. If so, such perceptions would lead to a decrease in shoppers' trust. Smart shelves could also have a negative impact on shared values, or the beliefs about what behaviors are appropriate, again resulting in lower trust.

Similarly, technologies that offload labor to shoppers might also have a negative impact on trust since they will likely lead to a perceived divergence in the retailer's and shoppers' perceptions about what procedures are appropriate in the exchange (shared values). By contrast, retail technological advancements that allow retailers to offer personalized promotions to their shoppers might contribute to building higher trust in the retailer-shopper relationships (Komiak and Benbasat 2006) since personalization might signal that the retailer is competent and helpful, qualities that are associated with higher trust (Altman and Taylor 1973).

*Relationship Commitment and Loyalty*

Relationship commitment refers to the belief of an exchange partner that a relationship with another party is so valuable that it deserves maximum effort to maintain it (e.g., Morgan and Hunt 1994). In other words, if a shopper is committed to the relationship she has with a particular retailer, she would believe that it is worth engaging in behaviors that ensure that the relationship continues, such as purchasing a greater share of her requirements for any given category from that retailer, purchasing categories from the focal retailer that she currently purchases from other retailers, and spreading positive WOM about the retailer.

The conceptualization of relationship commitment is also very similar to loyalty as pointed out by Morgan and Hunt (1994). Morgan and Hunt (1994) argue that relationship commitment is driven by (1) relationship terminations costs (all costs associated with dissolving an ongoing relationship, including any switching costs), (2) relationship benefits (what one gains from maintaining a relationship with another party), and (3) shared values (common beliefs about the appropriateness and importance of behaviors, procedures, and policies). In fact the definition of loyalty intentions is very similar to that of relationship commitment; specifically, loyalty intentions are defined as a willingness to perform a set of behaviors that signal one's desire to maintain an ongoing relationship with the retailer; such behaviors might include repeat purchasing and a larger share of wallet (Agustin and Singh 2005).

Shopper commitment and loyalty are of vital importance for the success of every retailer since loyal shoppers increase profitability by ensuring a consistent stream of revenues from both repeat and increased purchases and providing cost reductions (less promotional expenses). In fact, an improvement of five percent in customer retention/loyalty could increase firms' profits by 25%–85% depending on the industry (Kerin, Hartley, and Rudelius 2009). Therefore, when a retailer considers whether to adopt a retail technological innovation, one key consideration should be how such an implementation would impact shoppers' relationship commitment and loyalty. Given that one of the precursors of relationship commitment is the amount of relationship benefits, retail technological advancements that enhance shoppers' benefits from maintaining a relationship with the focal retailer (such as shopping apps that allow customers to prepare and save shopping lists, home delivery, and just-in-time personalized promotions) might have a positive impact on shoppers' commitment. This would make such technologies more appealing candidates for implementation by retailers relative to others that have a limited impact on relationship commitment and loyalty intentions.

*Privacy Concerns*

The rapid growth of technology has been a double-edged sword for retailers. On the one hand, it has allowed them to better tailor their products, messages, and service to customers' needs (Blattberg and Deighton 1991), leading to more cost-effective advertising and better customer retention (Deighton 1996). On the other hand, recent advances in retail technology have also significantly increased consumers' concerns that marketers might misuse their private information. In fact, privacy is reported to be one of the largest concerns for consumers in the United States (Lebo 2013) with most Americans believing that their privacy rights are "under serious threat" due to the large number of companies that collect personal information (CBS News 2005). Furthermore, retail technologies that are seen as too invasive of consumers' privacy lead to reactance that undermine their benefits (White 2004).

Information privacy refers to a person's ability to control the collection and use of individually identifiable personal information (Stone and Stone 1990). Consumers' privacy concerns usually arise from three distinct dimensions: *collection* of personal data, *control* over the use of personal information by firms, and *awareness* of privacy practices and how personal data are used (Malhotra, Kim, and Agarwal 2004; Smith, Milberg, and Burke 1996; Stewart and Segars 2002). Researchers have proposed that consumers engage in a *privacy calculus*, such that they compare the costs of providing personal information to the benefits they receive from marketers using their personal data (e.g., Klopfer and Rubenstein 1977; Posner 1981; Smith, Dinev, and Xu 2011; Stone and Stone 1990). Consumers' privacy concerns are mitigated and consumers are more willing to disclose information when they anticipate a "net benefit" from the privacy calculus (White 2004). For instance, Chellappa and Sin (2005) show that the value of personalization is about two times more important for consumers than privacy concerns in determining whether they use personalization services.

Consumers' privacy concerns have important implications for retailers and thus need to be considered seriously. Eastlick, Lotz, and Warrington (2006) show that privacy concerns negatively impact purchase intentions, while Bowie and Jamal (2006) find that firms perceived as "safe" or "trustworthy" with regards to consumers' information privacy have a competitive advantage. Given the significance of privacy concerns for determining shoppers' purchase behaviors, it is necessary for retailers considering new shopper-facing technologies to determine whether such initiatives would increase consumers' privacy concerns. Specifically, they should take into consideration the privacy calculus that consumers engage in and ensure that any new retail technologies provide more benefits for shoppers than the costs associated with giving up the necessary personal information for such technologies to work effectively. For instance, if retailers use technologies that invade shoppers' privacy, such as video cameras hidden in mannequins, but do not provide substantial benefits for shoppers in terms of customer service and in-store experience, this might lead to an increase in privacy concerns and backlash behaviors from shoppers. On the other hand, if shoppers gain significant benefits from retail technologies that use their personal information, such as personalized, just-in-time promotions, their privacy concerns should be mitigated.

*Shopper Reactions*

Once retailers assess the impact of various retail technologies on shoppers' perceptions, their next task is to understand shoppers' probable reactions. We suggest that the two key shopper reactions that should be of primary interest to retailers are (1) retailer patronage/switching, and (2) word-of-mouth (WOM).

*Retailer Patronage/Switching*

Shoppers' usually patronize multiple retailers to purchase their requirements for a given category (Luchs, Inman, and Shankar 2016); furthermore, shoppers tend to use different retailers to source their requirements for different categories (Inman, Shankar, and Ferraro 2004). Thus, customer share of wallet – or the amount of a shopper's spending that a retailer captures – is of great importance for retailers. In fact, Coyles and Gokey (2002) argue that focusing on improving share of wallet in addition to focusing only on retaining shoppers can add about ten times greater value to a company. Since shoppers' perceptions discussed earlier play an important role for determining purchase behavior, we argue that the implementation of retail technologies might prompt shoppers to decrease or increase the amount of their category requirements that they source from the focal retailer, as well as to switch different category purchases from or to that focal retailer. It is therefore important for retailers to assess potential changes in purchase behavior before implementing technological innovations on a large scale.

*WOM*

The adoption of retail technological innovations might also prompt shoppers to engage in either positive or negative WOM communications. Retailers need to measure the effects of their innovative actions on shoppers' WOM behavior because WOM plays a key role in determining shoppers' purchase decisions (Godes and Mayzlin 2009; Leskovec, Adamic, and Huberman 2007; Trusov, Bucklin, and Pauwels 2009). In fact, past research has shown that WOM can be more persuasive than traditional media channels (e.g., Godes and Mayzlin 2004; Herr, Kardes, and Kim 1991; Villanueva, Yoo, and Hanssens 2008). For example, Villanueva, Yoo, and Hanssens (2008) find that customers acquired through word-of-mouth contribute twice as much long-term value as those acquired through traditional channels. Given the importance of WOM for a firm's long-term profitability, retailers considering adoption of a new shopper-facing technology should pay attention to the potential effect on shoppers' WOM communications.

Next we describe a study in which we assessed shoppers' perceptions of and reactions to a sample of retail technologies to demonstrate how practitioners can use our shopper-focused decision framework when considering the adoption of a new retail technology. A core tenet of our shopper-focused technology adoption framework is that shopper reactions need to be considered. Thus, our study examines whether shopper perceptions would be affected by the adoption of a specific new technology and whether these reactions mediate behavioral intentions.

## Testing The Shopper-focused Decision Framework With a Sample of Retail Technologies

*Method*

Our approach is similar to the recent research by Aloysius et al. (2016) and Kleijnen, Ruyter, and Wetzels (2007) that examines shopper perceptions of mobile shopping. Our study used a six cell (technology: mobile app, proximity marketing, QueVision, Scan and Go, self-checkout, smart shelf technology) between-subjects design. Participants (n = 306, 47% male, $M_{age}$ = 39.9 years, $M_{hhincome}$ = $56,487) were recruited on Amazon's Mechanical Turk and completed the study in exchange for a small payment. Participants were randomly assigned to one of the six technology conditions. They were asked to imagine that their local grocery store had started using one of the six different retail technologies and were provided with a brief description of the capabilities of the technology. The full descriptions of all technologies can be found in the Appendix A.

Immediately after reading the information about the retail technology, participants completed a set of questions designed to assess their perceptions of the retailer (e.g., distributive fairness, value perceptions, privacy concerns, satisfaction, relationship trust, commitment, and loyalty) and their reactions in response to the implementation of the retail technology at their local grocery store (retailer patronage and WOM). Participants first completed the perceptions questions in a randomized order and then answered the reactions scales. All measures are available in Table 1. The study concluded with a set of demographic questions.

*Analysis and Results*

*Retailer Patronage Intentions/Purchase Likelihood*

A one-way ANOVA conducted on participants' retailer patronage intentions revealed that there are significant differences in participants' future purchase likelihood among the six different retail technologies ($F$(5, 295) = 8.15, $p$ < .0001). Post-hoc comparisons using the Bonferroni adjustment further reveal that the retailer's implementation of proximity marketing ($M$ = 4.48, $SD$ = 2.12) led to significantly lower future retailer patronage intentions than the use of mobile apps ($M$ = 5.76, $SD$ = 1.91; $p$ = .01), QueVision ($M$ = 6.57, $SD$ = 1.33; $p$ < .0001), or Scan and Go ($M$ = 5.73, $SD$ = 1.64; $p$ = .01). Furthermore, participants indicated significantly lower retailer patronage intentions when the retailer started using the smart shelf technology ($M$ = 4.74, $SD$ = 2.25) than QueVision ($p$ < .0001). The results of all ANOVAs and the Bonferroni tests, along with all means and standard deviations are displayed in Table 2. Finally, comparisons of the means of all six technologies to the scale midpoint (5 which refers to "no change in retailer patronage") reveal that mobile apps (t(49) = 2.81, $p$ = .007), QueVision (t(49) = 8.33, $p$ < .0001), Scan and Go (t(49) = 3.16, $p$ = .003), and self-checkout (t(50) = 1.93, $p$ = .06) all lead to a significant positive change in participants retailer patronage intentions; in contrast, the use of proximity marketing led to marginally significant negative change in retailer patronage (t(50) = −1.75, $p$ = .09); the smart shelf technology did not lead to any change ($p$ = .43).

*WOM*

A one-way ANOVA on participants' positive WOM intentions showed that there are significant differences among the six technologies ($F$(5, 295) = 7.16, $p$ < .0001). Specifically, participants were significantly less likely to engage in positive WOM behavior if a retailer starts using proximity marketing ($M$ = 4.46, $SD$ = 1.97) than mobile apps ($M$ = 5.75, $SD$ = 2.00; $p$ = .01), QueVision ($M$ = 6.51, $SD$ = 1.49; $p$ < .0001), or Scan and Go ($M$ = 5.82, $SD$ = 1.71; $p$ = .007). The implementation of the smart shelf technology ($M$ = 4.86, $SD$ = 2.39) also led to significantly lower WOM intentions than QueVision ($p$ = .0004). In addition, comparisons with the scale midpoint (5 which refers to "no change in WOM likelihood") show that the retailer's use of mobile apps (t(49) = 2.65, $p$ = .01), QueVision (t(49) = 7.18, $p$ < .0001), and Scan and Go (t(49) = 3.38, $p$ = .001) led to a significant increase in shopper' likelihood of generating positive WOM; self-checkout and smart shelf technology did not lead to any changes (both $p$*'s* > .12); by contrast, when a retailer implements proximity marketing, shoppers become less likely to generate positive WOM about the retailer than before (t(50) = −1.96, $p$ = .06).

Table 1
Measures.

| Construct | Measures | Cronbach's $\alpha$/r |
| --- | --- | --- |
| *Shoppers' perceptions* | | |
| Distributive fairness | *Adapted from* Maxham and Netemeyer (2003):<br>1. Given the investments I need to make to adopt this new technology (e.g., time, personal information, money), the final outcome that I will receive is fair.<br>2. The outcome of the retailer's implementation of this new technology is very positive for me.<br>3. Considering the inconvenience that this technology might cause me, the outcome that I will receive is more than fair.<br><br>(1 = Strongly disagree; 7 = Strongly agree) | Cronbach's $\alpha$ = .92 |
| Value perceptions | *Adapted from* Cronin, Brady, and Hult (2000):<br>Change in value resulting from technology implementation:<br>**Please indicate how the perceived value of this retailer to you would change as a result of adding this new technology. (1 = Would change extremely negatively; 5 = Would not change at all; 9 = Would change extremely positively)**<br>**Value perceptions:**<br>Compared to what I have to give up, the overall ability of this grocery retailer to satisfy my wants and needs is ___ (1 = Very low; 9 = Very high). | – |
| Privacy concerns | Privacy net benefits (benefits vs. risks; adapted from Xu et al. 2011):<br><br>1. I think my benefits gained from the use of this technology can offset the risk of my information disclosure.<br>2. The value I gain from using this technology is worth the information I give away.<br>3. I think the risks of my information disclosure will be greater than the benefits gained from the use of this technology. (R)<br><br>(1 = Strongly disagree; 7 = Strongly agree)<br>Privacy concerns (from van Doorn and Hoekstra 2013):<br>How concerned will you be about threats to your personal privacy when shopping at this grocery store after the implementation of this technology? (1 = Not concerned at all; 7 = Very concerned)<br>Perceived creepiness (from Barnard 2014):<br>To what extent do you think you'd feel in each of the following ways when grocery shopping at this retailer after the implementation of this technology?<br>1. Watched<br>2. Observed<br>3. Followed<br>4. Tracked<br>5. Spied On<br><br>(1 = Not at all; 7 = Very much) | Cronbach's $\alpha$ = .73<br>(privacy benefits vs. risks)<br>Cronbach's $\alpha$ = .96<br>(perceived creepiness) |
| Satisfaction | *Adapted from* Maxham and Netemeyer (2003):<br>Please indicate how your perceptions of the retailer would change as a result of adding this new technology:<br>My overall satisfaction with the retailer.<br>(1 = Would change extremely negatively; 5 = Would not change at all; 9 = Would change extremely positively) | – |

Table 1 (*Continued*)

| Construct | Measures | Cronbach's $\alpha$/r |
|---|---|---|
| Commitment | *Adapted from* Morgan and Hunt (1994):<br>Please indicate how your perceptions of the retailer would change as a result of adding this new technology:<br>1. My commitment to continue my relationship with the retailer<br>2. My belief that my relationship with this retailer deserves my maximum effort to maintain<br>3. My intent to maintain my relationship with this retailer indefinitely<br><br>(1 = Would change extremely negatively; 5 = Would not change at all; 9 = Would change extremely positively) | Cronbach's $\alpha$ = .94 |
| Trust | *Adapted from* Morgan and Hunt (1994):<br>Please indicate how your perceptions of the retailer would change as a result of adding this new technology:<br>1. My trust that this retailer can be counted on to do what is right<br>2. My belief that this retailer has high integrity<br><br>(1 = Would change extremely negatively; 5 = Would not change at all; 9 = Would change extremely positively) | r = .91, $p < .0001$ |
| Loyalty | *Adapted from* Maxham and Netemeyer (2003):<br>Please indicate how your perceptions of the retailer would change as a result of adding this new technology:<br>1. My loyalty towards this retailer<br>2. The extent to which I care about the long-term success of this store<br><br>(1 = Would change extremely negatively; 5 = Would not change at all; 9 = Would change extremely positively) | r = .91, $p < .0001$ |
| Shoppers' reactions | | |
| Retailer patronage/purchase likelihood | *Adapted from* Maxham and Netemeyer (2003):<br>Please indicate how your shopping behaviors with respect to this retailer would change as a result of the implementation of this new technology:<br>1. My willingness to purchase my groceries from this retailer would be ____ as a result of the implementation of this new technology.<br>2. My willingness to visit this store in the future would be ____ as a result of the implementation of this new technology.<br><br>(1 = Much lower than before; 5 = unchanged; 9 = Much higher than before) | r = .93, $p < .0001$ |
| WOM | *Adapted from* Maxham and Netemeyer (2003):<br>Please indicate how your shopping behaviors with respect to this retailer would change as a result of the implementation of this new technology:<br>1. My willingness to recommend this store to my relatives and friends would be _____ as a result of the implementation of this new technology.<br>2. My likelihood of saying good things about this store to my relatives and friends would be _____ as a result of the implementation of this new technology.<br><br>(1 = Much lower than before; 5 = unchanged; 9 = Much higher than before) | r = .95, $p < .0001$ |

Table 2
Results.

| Variable | Mobile app | | Proximity marketing | | QueVision | | Scan and Go | | Self-checkout | | Smart shelf technology | | ANOVA—main effect of technology condition |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | M | SD | M | SD | M | SD | M | SD | M | SD | M | SD | |
| Distributive fairness | $4.67^{**a}$ | 1.54 | $3.67^{a,b,c,d}$ | 1.61 | $5.43^{***b,e}$ | .91 | $4.68^{***c}$ | 1.20 | $4.71^{***d}$ | 1.47 | $4.06^{e}$ | 1.66 | $F(5, 296) = 9.10, p < .0001$ |
| Change in value perceptions | $5.94^{***}$ | 1.82 | $4.88^{a,b}$ | 1.91 | $6.94^{***a,c,d}$ | 1.42 | $6.04^{***b,e}$ | 1.66 | $5.80^{**c}$ | 1.89 | $4.90^{d,e}$ | 2.30 | $F(5, 297) = 8.83, p < .0001$ |
| Overall value perceptions | $6.02^{***}$ | 1.93 | $5.08^{***a,b}$ | 2.05 | $6.94^{***a,c}$ | 1.56 | $6.53^{***b,d}$ | 1.63 | $5.86^{***}$ | 1.88 | $5.40^{***c,d}$ | 2.04 | $F(5, 297) = 6.99, p < .0001$ |
| Change in satisfaction | $6.10^{***}$ | 1.87 | $4.96^{a,b}$ | 2.11 | $7.18^{***a,c,d}$ | 1.13 | $6.20^{***b,e}$ | 1.80 | $5.75^{*c}$ | 2.14 | $5.04^{d,e}$ | 2.52 | $F(5, 297) = 8.86, p < .0001$ |
| Privacy benefits vs. risks | $4.47^{*a,b}$ | 1.41 | $3.35^{**\ ,c,d,e}$ | 1.51 | $4.96^{***c,f}$ | 1.06 | $4.35^{d,g}$ | 1.26 | $4.35^{*e,h}$ | 1.08 | $3.44^{**b,f,g,h}$ | 1.23 | $F(5, 295) = 12.36, p < .0001$ |
| Privacy concerns | $3.78^{a}$ | 1.57 | $5.00^{***a,e}$ | 1.72 | $2.76^{***a,b,c}$ | 1.65 | $4.20^{b,d}$ | 1.53 | $2.96^{***d,e,f}$ | 1.72 | $4.69^{**c,f}$ | 1.61 | $F(5, 294) = 15.55, p < .0001$ |
| Creepiness | $3.78^{a,b}$ | 1.75 | $5.24^{***a,c,d,e}$ | 1.67 | $3.20^{***c,f}$ | 1.76 | $3.98^{d}$ | 1.82 | $3.04^{***e}$ | 1.74 | $5.00^{***b,f}$ | 1.58 | $F(5, 291) = 13.82, p < .0001$ |
| Change in commitment | $5.79^{**}$ | 1.70 | $4.78^{a}$ | 1.94 | $6.36^{***a,b}$ | 1.44 | $5.59^{*}$ | 1.82 | $5.61^{**}$ | 1.68 | $4.91^{b}$ | 2.51 | $F(5, 297) = 4.94, p < .001$ |
| Change in trust | $5.71^{**}$ | 1.83 | $4.82^{a}$ | 2.11 | $6.20^{***a,b}$ | 1.45 | $5.81^{***}$ | 1.72 | $5.56^{*}$ | 1.79 | $4.97^{b}$ | 2.53 | $F(5, 297) = 3.70, p = .003$ |
| Change in loyalty | $5.86^{**a}$ | 1.91 | $4.71^{a,b,c}$ | 2.01 | $6.44^{***b,d}$ | 1.41 | $6.02^{***c}$ | 1.84 | $5.50^{*}$ | 1.81 | $5.03^{d}$ | 2.53 | $F(5, 297) = 5.60, p < .0001$ |
| Change in purchase likelihood | $5.76^{**a}$ | 1.91 | $4.48^{a,b,c}$ | 2.12 | $6.57^{***b,d}$ | 1.33 | $5.73^{**c}$ | 1.64 | 5.51 | 1.89 | $4.74^{d}$ | 2.25 | $F(5, 295) = 8.15, p < .0001$ |
| Change in WOM | $5.75^{**a}$ | 2.00 | $4.46^{a,b,c}$ | 1.97 | $6.51^{***b,d}$ | 1.49 | $5.82^{***c}$ | 1.71 | 5.43 | 1.96 | $4.86^{d}$ | 2.39 | $F(5, 295) = 7.16, p < .0001$ |

Note: Means with the same superscripts in the same row are significantly different from each other at $p < .05$.
* $p < .05$ indicates whether the mean is significantly different from the scale midpoint.
** $p < .01$ indicates whether the mean is significantly different from the scale midpoint.
*** $p < .001$ indicates whether the mean is significantly different from the scale midpoint.

### *Shoppers' Perceptions*

We conducted separate one-way ANOVAs on each of the shoppers' perceptions predicted by the technology condition. We also conducted Bonferroni post-hoc tests of all pairwise differences to understand the differences in all shoppers' perceptions among the six different retail technologies. The results of all these separate one-way ANOVAs and the Bonferroni tests, along with all means and standard deviations are displayed in Table 2 (means with the same superscripts in the same row of Table 2 are significantly different from each other at $p < .05$). While we do not discuss the statistical results here for the sake of brevity, Fig. 5 plots the shopper attitudes and mean privacy concern for each technology. QueVision scores well (high on attitudes and low privacy concerns) on both dimensions, while smart shelves and proximity marketing are not viewed favorably by shoppers.

### *Mediation Analysis*

The constructs' measuring participants' perceptions of the different technologies tended to be highly correlated with one another (see Table 3). Due to this high correlation, we conducted a factor analysis in which we entered all items measuring the different shoppers' perceptions constructs (see Table 1 for all measures). This revealed only two factors: all items measuring distributive fairness, value, satisfaction, commitment, trust, loyalty and privacy net benefits loaded on one factor (factor loadings ranging from .69 to .92),[1] while the items measuring privacy concerns and creepiness loaded on a second factor (factor loadings ranging from .80 to .92). We averaged all items loading on the first factor (Cronbach's $\alpha = .98$) to create an index measure of shoppers' positive attitude towards the technology, and all items loading on the second factor (Cronbach's $\alpha = .96$) to create an index measure of shoppers' privacy concerns resulting from the implementation of the technology.

Two separate one-way ANOVAs revealed that there were significant differences in both shoppers' positive attitude ($F(5, 295) = 7.88$, $p < .0001$) and privacy concerns ($F(5, 290) = 14.94$, $p < .0001$) among the six different technologies. The post-hoc Bonferroni adjusted pairwise comparisons revealed that participants' had significantly less positive attitudes towards proximity marketing ($M = 4.35$, $SD = 1.75$) than towards mobile apps ($M = 5.41$, $SD = 1.60$; $p = .02$), QueVision ($M = 6.10$, $SD = 1.04$; $p < .0001$), and Scan and Go ($M = 5.41$, $SD = 1.44$; $p = .02$), and marginally less positive than those towards self-checkout ($M = 5.25$, $SD = 1.52$; $p = .08$). Participants also indicated more positive attitudes towards QueVision than towards the smart shelf technology ($M = 4.56$, $SD = 2.10$; $p < .0001$). In addition, the retailer's use of proximity marketing ($M = 5.20$, $SD = 1.61$) generated significantly greater privacy concerns than the use of mobile apps ($M = 3.78$, $SD = 1.67$; $p < .001$), QueVi-

[1] One item from the privacy net benefits scale (i.e., "I think the risks of my information disclosure will be greater than the benefits gained from the use of this technology. (R)) did not have high loadings on any of the two factors (factor loadings: .18 for the first factor and −.32 for the second factor) and thus was dropped from the analysis.

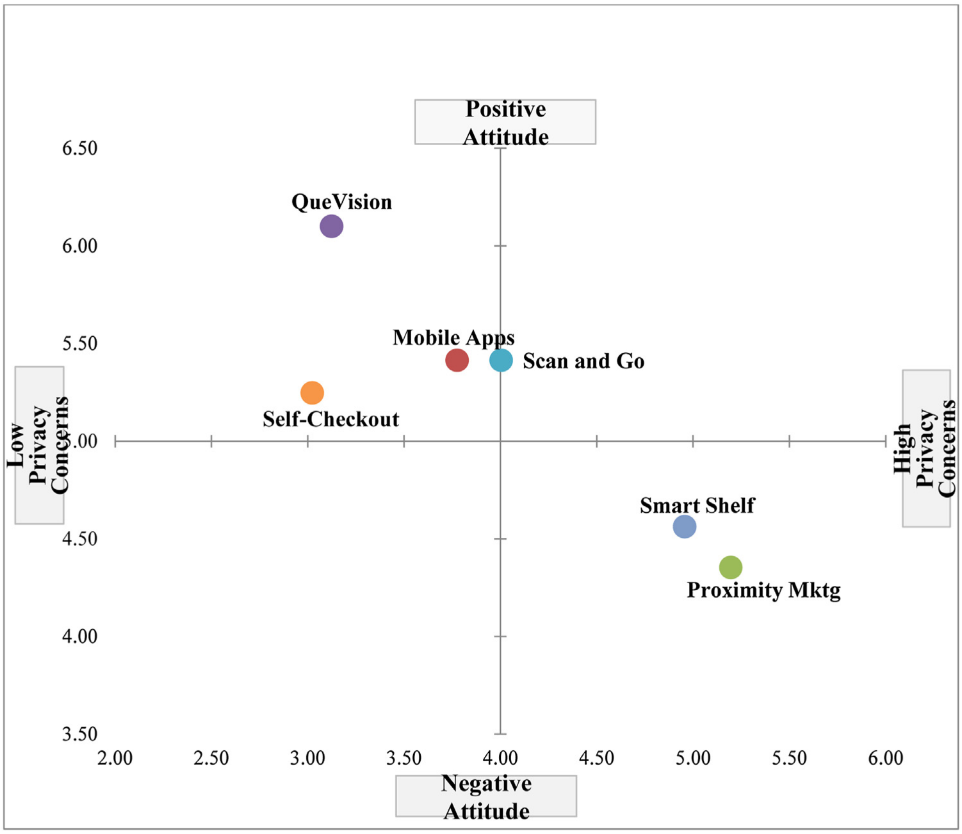


Fig. 5. Shopper attitudes and privacy concerns of new retail technologies.

Table 3
Correlation matrix.

| Construct | Construct # | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Distributive fairness | 1 | 1.00 | – | – | – | – | – | – | – | – | – | – | |
| Change in value perceptions | 2 | .819*** | 1.00 | – | – | – | – | – | – | – | – | – | |
| Overall value perceptions | 3 | .769*** | .804*** | 1.00 | – | – | – | – | – | – | – | – | |
| Privacy benefits vs. risks | 4 | .751*** | .692*** | .650*** | 1.00 | – | – | – | – | – | – | – | |
| Privacy concerns | 5 | −.570*** | −.513*** | −.465*** | −.633*** | 1.00 | – | – | – | – | – | – | |
| Creepiness | 6 | −.545*** | −.495*** | −.408*** | −.562*** | .802*** | 1.00 | – | – | – | – | – | |
| Change in satisfaction | 7 | .841*** | .885*** | .792*** | .703*** | −.513*** | −.490*** | 1.00 | – | – | – | – | |
| Change in commitment | 8 | .806*** | .832*** | .767*** | .689*** | −.505*** | −.486*** | .886*** | 1.00 | – | – | – | |
| Change in trust | 9 | .779*** | .776*** | .732*** | .645*** | −.493*** | −.474*** | .834*** | .871*** | 1.00 | – | – | |
| Change in loyalty | 10 | .824*** | .836*** | .776*** | .692*** | −.499*** | −.488*** | .887*** | .918*** | .930*** | 1.00 | – | |
| Change in purchase likelihood | 11 | .842*** | .881*** | .775*** | .718*** | −.567*** | −.547*** | .875*** | .853*** | .814*** | .870*** | 1.00 | |
| Change in WOM | 12 | .815*** | .840*** | .755*** | .706*** | −.568*** | −.527*** | .867*** | .865*** | .838*** | .880*** | .926*** | 1.00 |

*$p < .05$; **$p < .01$; ***$p < .0001$.

sion ($M = 3.12$, $SD = 1.67$; $p < .0001$), Scan and Go ($M = 4.00$, $SD = 1.73$; $p = .006$), and self-checkout ($M = 3.02$, $SD = 1.68$; $p < .0001$). Similarly, the implementation of the smart shelf technology ($M = 4.96$, $SD = 1.55$) led to significantly greater privacy concerns than the implementation of mobile apps ($p = .01$), QueVision ($p < .0001$), and self-checkout ($p < .0001$), as well as marginally greater privacy concerns than the use of Scan and Go ($p = .08$). Finally, participants indicated greater privacy concerns with Scan and Go than self-checkout ($p = .05$).

A mediation analysis conducted using bootstrapping (Hayes 2012; Model 4 with the appropriate adjustment for handling a categorical independent variable) on participants' retailer patronage intentions predicted by the technology condition with shoppers' attitude and privacy concerns as mediators operating in parallel demonstrated that both positive attitude toward the technology (indirect effect: $b = .12$, $SE = .04$, 95% CI: .043, .177) and the privacy concerns resulting from the implementation of the technology (indirect effect: $b = -.02$, $SE = .01$, 95% CI: −.035, −.002) emerged as significant full mediators (direct effect: $p = .86$). A similar mediation analysis run on participants positive WOM intentions revealed that only shoppers' positive attitude (indirect effect: $b = .12$, $SE = .04$, 95% CI: .049, .187) fully mediated the relationship between the technology condition and WOM (direct effect: $p = .54$); privacy concerns did not emerge as a significant mediator of the effect of technology on shoppers' WOM intentions (indirect effect: $b = -.01$, $SE = .01$, 95% CI: $-.031$, .001).

## Discussion

Shopper-facing technology plays an important role in increasing revenues and decreasing costs. In this article, we have discussed some of the most disruptive retail technologies over the past few years, plus technologies that are beginning to gain traction in retailers today. Additionally, we presented the current decision calculus that sophisticated retailers use when considering a new shopper-facing technology and noted that new technologies provide value by either (1) increasing revenue through drawing new shoppers, increasing share of volume from existing shoppers, extracting greater consumer surplus (e.g., charging higher prices to shoppers who have a higher willingness to pay), or increasing supplier payments; or (2) decreasing costs through offloading labor to shoppers or automation.

Our findings support our central thesis that retailers' evaluation process of new shopper-facing technology needs to be expanded beyond what the technology **can** potentially deliver to consider shopper reactions and assess what the technology **will** deliver. We argue that the present decision calculus is insufficient in that shopper perceptions of the new technology and their reaction thereto need to be considered. Specifically, shoppers update their perceptions of fairness, value, satisfaction, trust, commitment, and attitudinal loyalty, and evaluate the potential intrusiveness of the technology on their personal privacy. These perceptions then mediate the effect of the technology on shopper behavioral reactions such as retail patronage intentions and WOM communication.

We provide preliminary support for our framework by examining consumers' perceptions of several retail technologies, as well as their behavioral intentions. The findings show that shopper perceptions of the retailer are affected by new shopper-facing technologies and that these reactions mediate behavioral intentions. To be specific, our study reveals that technology adoption does have a significant impact on two key shoppers' behaviors—their future retailer patronage intentions and their willingness to generate positive WOM about the retailer. Furthermore, in support of our shopper-focused decision calculus, the results demonstrate that shoppers' attitudes towards each technology (comprised of a shift in perceptions of distributive fairness, satisfaction, value perceptions, trust, commitment, and loyalty) and their privacy concerns mediate the effect of technology adoption on purchase likelihood. Interestingly, only attitudes emerged as a mediator of technology on WOM intentions. These results suggest that retailers do need to take shoppers' attitudes into consideration to gauge the potential success of any large scale technology adoption because differences in attitudes do indeed drive future purchase likelihood and positive WOM intentions—two shoppers' behaviors that are critical for the success of any retailer.

As mentioned above, our findings also help to calibrate each technology vis-à-vis its potential to deliver on its value proposition in the framework. For example, proximity marketing seeks to provide value by increasing basket size in the short run and attracting new shoppers in the longer run. However, as shown in Table 2, our respondents reacted rather negatively to this technology. It received a "double whammy" of the lowest score in terms of attitudinal perceptions (e.g., fairness, value) and the highest privacy concerns. Clearly, shoppers have serious reservations about proximity marketing and these concerns need to be overcome in order for proximity marketing to deliver on its promise. At present, what proximity marketing **will** deliver to retailers in terms of positive ROI seems to fall well short of what it potentially **can** deliver.

In contrast, QueVision generated the most positive attitudinal perceptions and did not generate privacy concerns. By reducing shoppers' wait time, this technology offers the potential to increase share of wallet of current shoppers and attract new shoppers through positive WOM. However, since QueVision is largely invisible to the shopper, the retailer should make sure that shoppers are aware of it and its benefits in order to maximize positive shopper outcomes.

One key advantage of our framework is that by assessing shoppers' potential attitudinal shifts, privacy concerns, and behavioral reactions, the retailer can be forewarned. At that point, the forecasted incremental revenues, cost savings, or both can be adjusted and the retailer can take action to mitigate potential issues. For example, a retailer that is rolling out proximity marketing might be well advised to proactively address shoppers' concerns about surveillance and invasions of privacy. The retailer could provide a list of the advantages of the new technology (e.g., discounts on relevant products) and only offer the program to shoppers who opt in.

We note that the demonstrated mediating effects of shoppers' perceptions of the impact of retail technologies on shoppers' behavioral reactions are contingent on shoppers' adoption of the technology. While some of the technologies that we have discussed thus far do not depend on shopper adoption, most of them rely on shoppers' adopting and actively utilizing the technology in order for the benefits to the retailer to be realized. On the one hand, QueVision is largely invisible to shoppers but leads to beneficial shopper outcomes such as faster checkout and greater availability of parking—assuming that there are extra employees who can be allocated to the checkout lanes when needed. On the other hand, the benefits of technologies such as self-checkout and scan-and-go are completely dependent on shopper utilization.

According to the technology acceptance model (TAM) introduced by Davis, Bagozzi, and Warshaw (1989) and Davis (1989), acceptance and use of new information technology systems is a function of the perceived usefulness of the technology and its perceived ease of use. While the TAM was initially developed to explicate the process driving users' acceptance of information technology in work settings, some researchers have employed the TAM to explore consumer settings (e.g., Chen, Wu, and Li 2014). Perceived usefulness and ease of use have both been associated with greater usage intentions, although perceived usefulness seems to be more strongly correlated to usage intentions (e.g., Szajna 1996).

The criticality of shopper adoption to the success of new retail technologies implies that retailers need to assess shoppers' perceptions of a potential new technology's usefulness, ease of use, and adoption likelihood before testing our proposed shopper-focused decision framework. Consequently, we conducted a supplementary study in which we assessed the usefulness, ease of use, and adoption likelihood of the sample of retail technologies we tested in our empirical work. The results of this study confirmed that all retail technologies (i.e., mobile app, proximity marketing, QueVision, Scan and Go, self-checkout, smart shelf technology) had relatively high usefulness, ease of use, and adoption likelihood (all means were significantly greater than the scale midpoint, all $p$'s < .001. The only exception was the adoption likelihood for proximity marketing, which was not significantly different from the scale midpoint, $p = .25$). The full results of this study are reported in Appendix B. In sum, while the sample of retail technologies we used to demonstrate how practitioners can use our framework have relatively high usefulness, ease of use and adoption likelihood (with the exception of proximity marketing), this study underscores the importance for retailers to assess these assumptions before applying our shopper-focused decision framework. The set of measures that can be used by practitioners to examine retail technologies' ease of use, usefulness, and adoption likelihood can be found in Appendix B.

Future research needs to test our entire framework and identify ways in which shoppers can be convinced to adopt new retail technologies and learn how to use them effectively. Additionally, the benefits of a new retail technology can be assessed via a quasi-experiment event study paradigm. That is, the retailer can implement the new technology in a sample of stores and the resulting shifts in shopper response (e.g., basket size, price paid) can be compared against a matched sample. These results can then be used to estimate the ROI of the technology.

Shopper-facing technology is particularly important to retailers, as it offers direct impacts on revenues and costs. Hopefully, the shopper-centric decision calculus presented in this article will be useful to retailers as they sift through the many options that are available in order to more effectively allocate their scarce resources. While it represents a start, our work is obviously not the last word on this important topic, and we encourage other researchers to contribute toward improving the development, assessment, and roll out of new technologies that create positive outcomes for both retailers and shoppers.

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## Appendix A. Descriptions of all retail technologies

Panel A: Mobile app.

The mobile app allows retailers to advertise directly to shoppers, provide online in-store navigation, and enhance customers' shopping experience. The benefits of the use of mobile apps for retailers are as follows:

1. Send personalized promotions and messages to shoppers—retailers can use beacons to target customers with personalized offers by syncing customers' shopping lists, wishlists, and favorites with their app.
2. Provide in-store navigation without the need for additional staff—the mobile apps can help customers locate various aisles and specific products they wish to purchase, thus saving retailers a lot of labor costs;
3. Increase sales through the In-Store Pick-Up Option—using the mobile app, customers can order the products online and pick them up in the store later. Thanks to the use of beacons, when a customer who has placed an order for in-store pick-up is in the vicinity of the store, the store staff prepares the order and makes sure that it is ready for picking up, thus saving the customer a lot of time. The customer is notified via push notifications when the order is ready for pick-up.

Panel B: Proximity marketing.

Proximity marketing technology combines smart phone technology and loyalty card data, and allows retailers to reach shoppers with personalized offers in real time by tracking their position in the store through their smartphone. The platform collects continuous feedback during each shopper's trip and uses sensor readings from shoppers' smartphones to calculate position and movement. Then, the retailer can deliver relevant messages and offers at key moments of the shopping trip. The benefit of Proximity Marketing technology for retailers is increased redemption of promotional offers since shoppers receive the offers at the key time.

Panel C: QueVision.

QueVision is a new technology whereby automatic traffic counters are installed at the store entrance and compared to the number of people checking out in order to estimate the number of checkout lanes that need to be opened in order to manage shoppers' wait time in line.
The benefits of QueVision for retailers are as follows:

1. Service customers more quickly and reduce their wait time in the store.
2. Allow customers to spend more time shopping in the stores rather than waiting in line, which increases the retailers' revenues.
3. Free up parking space especially in urban areas where parking space is usually very limited, thus increasing store traffic and lowering costs.

Panel D: Scan and Go.

Scan and Go is a technology that allows shoppers to use their smartphone to scan items as they put them in their basket. Shoppers can then use the scanned data via the retailer's app to pay without having to scan the items again at the checkout line.
The benefit of the Scan and Go technology for retailers is that it:

1. Provides them with labor cost savings from reducing the number of cashier lanes that need to be open at a certain period of time.
2. Helps retailers service customers more quickly and reduce their wait time in store.

Panel E: Self-checkout

Self-checkout is an automated process that enables shoppers to scan, bag, and pay for their purchases without the need for a cashier.
The benefit of self-checkout for retailers is that it allows them to reduce their labor costs by servicing more customers with fewer cashiers.

Panel F: Smart shelf technology

Smart shelf technology allows retailers to keep track of inventory, advertise directly to shoppers, and update prices in real time.
The benefits of smart shelves for retailers are as follows:

1. Reduce out-of-stocks—a weight-sensitive mat is placed on the shelf and a notification is sent to store personnel when the last item is removed. If reserve stock is on hand, the shelf is restocked quickly.
2. Send personalized promotions and messages to shoppers at the time of shopping—smart shelf technology uses beacons which are proximity-based communication devices that use low-energy Bluetooth technology to send personalized messages and promotions to shoppers' smartphones.
3. Change prices remotely and dynamically—the smart shelves are equipped with digital price tags which enable retailers to change prices remotely, thus saving them a lot of labor costs; furthermore, the digital price tags also allow retailers to change prices dynamically based on demand at time of year, day of week, and even time of day and based on shoppers' willingness to pay (i.e., lower prices when demand is low to avoid excessive inventory or increase prices when demand is high). Thus, retailers are able to "optimize" the price to increase revenues.

## Appendix B. Supplementary study testing the technology adoption model

### *Method*

This study used a 6 group (technology: mobile app, proximity marketing, QueVision, Scan and Go, self-checkout, smart shelf technology) between-subjects design. Participants ($n = 302$, 50% male, $M_{age} = 35.8$ years, $M_{hhincome} = \$52,055$) were recruited on Amazon's Mechanical Turk and completed the study in exchange for a small payment. As in our main study, participants were randomly assigned to one of the six technology conditions. Participants were asked to imagine that their local grocery store had started using a new technology and read a short description of the technology and its capabilities. We used the same descriptions of all technologies as in our main study (see Appendix A).

Participants then completed a set of questions that assessed the ease of use ("I believe that my interaction with this technology will be clear and understandable," "It will be easy for me to become skillful in using this technology," and "I would find this technology easy to use in the store," where 1 = "Strongly Disagree" and 7 = "Strongly Agree;" $\alpha = .92$; Venkatesh et al. 2003), usefulness ("I believe that having this technology in the store will be a useful experience," "I believe that having this technology in the store will add additional value to my shopping experience," and "I believe that having this technology in the store will add value to the overall service," where 1 = "Strongly Disagree" and 7 = "Strongly Agree;" $\alpha = .95$; Froehle and Roth 2004), and adoption likelihood ("How likely are you to use this new technology if it were available in your grocery store?", where 1 = "Not Likely At All" and 7 = "Very Likely") of the technology presented to them. The order of the questions was randomized. The study concluded with a set of demographic questions.

### *Analysis and Results*

#### *Ease of Use*

First, comparisons of the ease of use of each technology to the scale midpoint revealed that all six technologies had relatively high ease of use (all $p$'s $< .001$). All means, standard deviations, and significance levels for all comparisons are presented in Table B1. Furthermore, a one-way ANOVA conducted on participants' perceptions of the ease of use of each technology revealed that there were only marginally significant differences among the technologies ($F(5, 296) = 2.14$, $p = .06$). However, post-hoc pairwise comparisons using the Bonferroni adjustment revealed no significant differences among any of the six retail technologies.

#### *Usefulness*

Comparisons of the perceived usefulness of each technology to the scale midpoint also revealed that participants perceived that all six technologies had relatively high usefulness (all $p$'s $< .001$; see Table B1 for all means and standard deviations). A one-way ANOVA on the technology usefulness showed significant differences among the six technologies ($F(5, 295) = 3.89$, $p = .002$). The Bonferroni-adjusted post-hoc comparisons demonstrated that the QueVision technology ($M = 5.95$, $SD = .90$) had significantly higher usefulness than proximity marketing ($M = 4.81$, $SD = 1.60$; $p = .001$). All other pairwise comparisons were not significant.

#### *Adoption Likelihood*

The mean adoption likelihoods of mobile apps, QueVision, Scan and Go, self-checkout, and the smart shelf technology were all significantly higher than the scale midpoint (all $p$'s $< .001$). However, the adoption likelihood of proximity marketing ($M = 4.39$, $SD = 1.96$) was not significantly different from the scale midpoint ($p = .25$). In addition, we conducted a one-way ANOVA on the adoption likelihood, which revealed significant differences among the six technology conditions ($F(5, 295) = 4.41$, $p < .001$). The post-hoc pairwise comparisons using the Bonferroni adjustment revealed that proximity marketing had significantly lower adoption likelihood than both QueVision ($M = 5.78$, $SD = 1.07$; $p = .001$) and self-checkout ($M = 5.62$, $SD = 1.68$; $p = .003$). All other pairwise comparisons were not significant.

Finally, we also conducted a mediation analysis using bootstrapping (Hayes 2012; Model 4) on technology adoption likelihood predicted by the technology condition with perceived ease of use and usefulness as mediators operating in parallel. Results showed that perceived usefulness emerged as a significant partial mediator (indirect effect: $b = .04$, $SE = .02$, 95% CI: .0004, .0672; direct effect: $F(5, 292) = 4.37$, $p = .001$), while perceived ease of use did not mediate the relationship between the

Table B1
Supplementary study results.

| Variable | Mobile app | | Proximity marketing | | QueVision | | Scan and Go | | Self-checkout | | Smart shelf technology | | ANOVA—main effect of technology condition |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | M | SD | M | SD | M | SD | M | SD | M | SD | M | SD | |
| Ease of use | 5.78*** | 1.17 | 5.23*** | 1.23 | 5.77*** | .93 | 5.84*** | 1.05 | 5.73*** | 1.20 | 5.46*** | 1.31 | $F(5, 296) = 2.14$, $p = .06$ |
| Usefulness | 5.57*** | 1.39 | 4.81***a | 1.60 | 5.95***a | .90 | 5.43*** | 1.21 | 5.16*** | 1.59 | 5.14*** | 1.68 | $F(5, 295) = 3.89$, $p = .002$ |
| Adoption likelihood | 5.31*** | 1.73 | 4.32a,b | 1.96 | 5.78***a | 1.07 | 5.30*** | 1.72 | 5.62***b | 1.68 | 5.10*** | 2.02 | $F(5, 295) = 4.41$, $p < .001$ |

Note: (1) ** $p < .01$, * $p < .05$ indicates whether the mean is significantly different from the scale midpoint. (2) Means with the same superscripts in the same row are significantly different from each other at $p < .05$.
*** $p < .001$ indicates whether the mean is significantly different from the scale midpoint.

technology condition and adoption likelihood (indirect effect: $b = .007$, $SE = .01$, 95% CI: −.005, .018).

*Discussion*

In sum, the results of this supplementary study indicate that all six retail technologies chosen to demonstrate the use of the proposed shopper-focused decision framework have relatively high perceived ease of use, usefulness, and adoption likelihood. The only exception was proximity marketing, which had an average likelihood of adoption. This result is consistent with the results obtained in our main study in which proximity marketing had the lowest positive attitude score and highest privacy concerns score across the six technologies examined. Finally, in line with prior research (Chen, Wu, and Li 2014), this supplementary study showed that the technology adoption likelihood is primarily driven by perceived technology usefulness but not by perceived ease of use.

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