

Refractive Surveillance: Monitoring Customers to Manage Workers

KAREN LEVY¹
SOLON BAROCAS
Cornell University, USA

Collecting information about one group can facilitate control over an entirely different group—a phenomenon we term *refractive surveillance*. We explore this dynamic in the context of retail stores by investigating how retailers' collection of data about customers facilitates new forms of managerial control over workers. We identify four mechanisms through which refractive surveillance might occur in retail work, involving dynamic labor scheduling, new forms of evaluation, externalization of worker knowledge, and replacement through customer self-service. Our research suggests that the effects of surveillance cannot be fully understood without considering how populations might be managed on the basis of data collected about others.

Keywords: surveillance, privacy, inequality, retail, consumers, labor, management

Workers across sectors are increasingly subject to electronic monitoring of various forms, facilitating more intensive management; meanwhile, ever-increasing amounts of data are being collected about consumers, affecting their treatment in the marketplace. Both of these have drawn the concern of scholars, advocates, and regulators. In each, the fundamental concern regards how surveillance renders a group more vulnerable to control.

However, surveillance can be *refractive*: Monitoring of one party can facilitate control over another party that is not the direct target of data collection. In this article, we describe how such refractive dynamics apply to the relationship between consumer monitoring and worker management. Retailers have begun to use technologies and managerial techniques that integrate broad swaths of data about customers' behaviors and propensities into the dynamic management of workers' conditions of

Karen Levy: karen.levy@cornell.edu
Solon Barocas: sbarocas@cornell.edu
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employment. We identify and describe the mechanisms through which data collected about consumers can implicate the economic interests of workers, particularly those in the low-wage retail labor market.

In drawing attention to these refractive dynamics, we provide a much richer account of the interdependent and relational nature of privacy and the role that information plays in economic inequality. In certain cases, workers' economic prospects may be more dependent on what firms can learn about consumers than what firms can learn about workers themselves. Indeed, focusing on the privacy experience of poor populations in isolation risks missing that low-wage workers' economic status may depend on information that retailers can collect about more privileged groups.

Our article proceeds as follows. To begin, we explain how common models limit the inquiry about the parties and interests implicated by surveillance, and propose a new model that allows privacy to speak more broadly to questions of economic inequality. Then, we apply our model in the context of emerging technologies and management strategies in retail stores, identifying four primary mechanisms through which retailers' data collection about customers influences the management of workers. We then consider how these possibilities play out in practice. To close, we consider the broader utility of the concept of refractive surveillance across domains.

From Dyadic to Refractive Surveillance

The simplest and most common model of surveillant relationships is dyadic: Surveillance is exercised by an observer as a means of gathering information about, and enacting control over, an observed. In this model, observation is a direct corollary to control, and privacy is understood as an individual's ability to limit or neutralize the observer's power (Solove, 2006; Westin, 2015). This highly stylized model of surveillance has been thoroughly critiqued and complicated in existing scholarship, giving rise to a long list of neologisms: *panopticism* (internalizing the gaze of another and therefore watching oneself; Foucault, 1975), *synopticon* (the many watching the few; Lyon, 2006), *lateral surveillance* (peers watching each other; Andrejevic, 2002; Marwick, 2012), and *sousveillance* (watching the watchers; Mann, Nolan, & Wellman, 2002), to name just a few. As this and other work have established, the surveillant gaze is multivalent and can point in many directions, sometimes even more than one at the same time. However, even these theoretical accounts of surveillance are premised, fundamentally, on a tight coupling between the object of observation and the control thereby exercised over the person observed.

Although an intuitive and appealing way to understand surveillance, this model fails to capture the fact that observation can also be decoupled from control, such that information collected about one party is brought to bear on another. In this way, data collection can impact the interests of people other than the direct target of surveillance. We call this dynamic *refractive surveillance* (see Figure 1). This model broadens our understanding of the range of parties implicated by surveillance (but who may not be its ostensible target) as well as its effects (which extend beyond those typically understood as privacy harms).

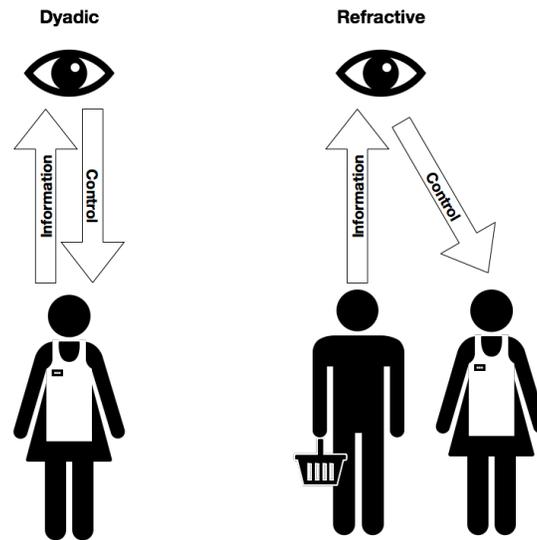


Figure 1. Dyadic versus refractive surveillance.

The dyadic model fails to explicitly acknowledge the interdependent social nature of privacy—a notion recognized in other recent scholarship (Marwick & boyd, 2014; Roessler & Mokrosinska, 2015; Taylor, Floridi, & van der Sloot, 2017)—and hence may not capture the full range of actors and interests implicated by surveillance. Privacy protections premised on the dyadic model have also proven a poor fit for addressing issues of social and economic justice, leading some scholars to downplay privacy in order to focus more explicitly on concepts such as fairness and discrimination (Dwork & Mulligan, 2013; Gandy, 1993, 1995; Newman, 2015). Refractive surveillance, in contrast, allows privacy to speak more directly to questions of economic justice. Methodologically, this reframing calls on us as researchers to consider information flows and constraints within a broader ecology of actors and interests.

Customer Tracking and Low-Wage Retail Workers

We apply our framework to a specific setting: the low-wage retail workplace. Retail workplaces employ more than 28 million Americans and account for 17% of the total wages, salaries, and benefits paid to workers in the United States (Retail Info Systems News, 2012); approximately one in 10 Americans works in retail (Corkery, 2017). The retail workforce is notably diverse: Retail is the second most common industry in which Black workers are employed, and roughly half of retail workers are women (Ruetschlin & Asante-Muhammad, 2015).

As low-wage workplaces, retail stores are sites of significant surveillance—both historically and in emerging forms—for purposes of worker management (Bernstein, 2017). At the same time, retail stores have become places of intensifying data collection about consumers and their preferences and behaviors (Turow, 2017). Like workplace surveillance, in-store customer tracking has attracted growing attention

and criticism from privacy advocates. A recent *Guardian* exposé about Saks Fifth Avenue's use of facial recognition cameras prompted significant blowback from privacy scholars, who called out the retailer for transparency and security concerns (Frey, 2016). Data protection authorities and advocates, prompted by the emergence of Wi-Fi tracking and video analytics in stores, have issued a number of recent recommendations for best practices in these areas (International Working Group on Data Protection in Telecommunications, 2015a, 2015b; UK Information Commissioner's Office, 2016), as well as guides for consumers about how to opt out of collection when possible (Gray, 2015).

Despite growing attention to the effects of in-store customer-tracking technologies on customers' interests, we are not aware of any work that considers the impacts of these technologies on workers. There is an urgent need to consider how the wide-ranging data collected about customer behaviors facilitate firms' dynamic management of workers' conditions of employment. Dyadic models of customer surveillance would tend to focus neither on the worker as a party implicated by customer data collection nor on the economic impact of the emerging labor management practices that depend on these data. Understanding retail surveillance as a case of refractive surveillance broadens the traditional inquiry to more fully account for the dynamics introduced by these new technologies.

One important note is in order. The analysis that follows addresses the newest and most sophisticated data-gathering and management systems currently being marketed to retailers, as described by technology vendors, the trade press, industry white papers, and other sources. We do not attempt to present an empirical assessment of the current prevalence of these technologies in retail stores, nor do we assess the complexities inherent in their on-the-ground implementation. The technologies and practices discussed here should be understood to represent an aspirational model of the near future of retail and how such a future might manifest new forms of refractive surveillance.

The Retail Technology Landscape

Retail tracking of customers has exploded in recent years (Turow, 2017). Within the industry, increased customer tracking has roots in the "retail crisis" being experienced by brick-and-mortar chains: Concerns about commerce moving online have motivated retail stores to find strategies to retain relevance and maintain sales. The great majority of current retail sales—roughly 90% of the \$3.7 trillion in the United States annually—still takes place in brick-and-mortar stores rather than online (EKN Research, 2016); however, the proportion of online sales continues to increase, and is perceived as a growing threat to the traditional retail model.

Much of this concern is predicated on shifting knowledge bases among retail consumers. Consumers now have greater access to different retail options, as well as more information about the products they seek, including prices offered by competing retailers. This access means that consumers are equipped to do more comparison shopping, and may see less value added by the in-store retail experience; in one industry survey, 60% of consumers reported that they felt they knew more about the products they were seeking than store associates, and one in two store associates believed that shoppers were better connected to product information than the associates themselves were (EKN Research, 2016).

These dynamics create a twofold business rationale for brick-and-mortar stores' tracking of customers. First, retailers seek to approximate the amount of data collection that occurs easily in e-commerce (e.g., what products consumers look at and for how long, what products are put in a shopping cart and then removed) by deploying a variety of sensors and other technologies to capture analogous information in physical stores (Nowak, 2015). Second, retailers are trying to address the perceived "knowledge deficiency gap" between store associates and customers, who often know more about products and prices than workers do (Kohan, 2015). Brick-and-mortar retailers, then, view data collection about customers as an attempt to "catch up" with both online retailing and a more informed customer base. As a result, an enormous variety of technologies is used to capture ever more data about customers and their activities, both within and outside stores. These technologies include sensors that track customers' locations and activities on the retail floor, pull data from customers' behaviors in other locations or on other platforms, draw on customers' social media posts to create affective profiles, and many other systems (see Figure 2) (for a more exhaustive overview, see CB Insights, 2016).

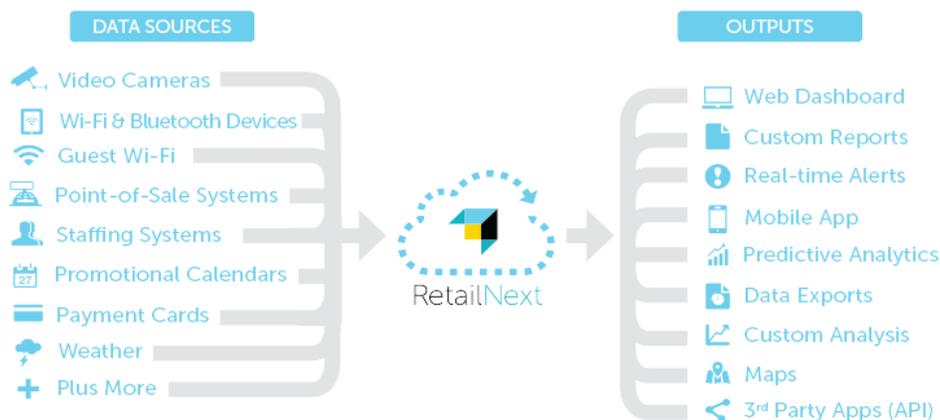


Figure 2. RetailNext and other vendors integrate multiple data sources for operational analysis (RetailNext, n.d.).

In-Store Location Sensing and Kinetic Mapping

Perhaps the most fundamental data collection technology in this arena is the use of sensors, beacons, and cameras that map a customer's physical location and movements in a retail store. Retailers have long kept counts of the number of customers entering their stores, often through electronic "people counters" at the front doors (Retail Info Systems News, 2012). But digital technologies have evolved considerably to give retailers access to more fine-grained data on customer movements. Some technologies generate spatial data, often enabled by the fact that customers universally carry cell phones. Retailers install wireless access points that create Wi-Fi hotspots in and around their brick-and-mortar stores, with the goal of registering the presence of customers' mobile devices. As mobile devices passively scan for nearby Wi-Fi networks, they communicate uniquely identifying information to the wireless access point. Retailers rely on beacons that connect to phones via Bluetooth for similar purposes. Each of these

technologies enables reidentification of a shopper over multiple trips. And if a shopper chooses to connect to a retailer's wireless network, data can also be gathered about the shopper's online behavior.

Video cameras facilitate customer tracking as well and may be augmented by facial detection technologies and video analytics, which can infer demographic information about customers (e.g., gender, race, age). For example, one vendor "uses Wi-Fi and touch-screen analytics for shopper behavior (visit history, duration, in-store and on-screen product browsing) combined with facial analytics for characteristics (gender, age, mood) to best understand and anticipate shopper interests" (eyeQ, Inc., 2014, p. 3). Other emerging location-tracking technologies include "audio beacons" that detect pings via a phone's microphone, and LED signals from special light fixtures, detectable by a phone's camera (Gray, 2015). New technologies on the market "fuse" video analytics, Wi-Fi, and Bluetooth capabilities into a single sensor, which merges the unique capabilities of each (RetailNext, n.d.).

By pinpointing customers' locations within a retail store, retailers can learn quite a bit about how customers engage with products, displays, and store associates. Through kinetic mapping, retailers visualize customers' paths through stores to understand "dwell time" in front of products—the products that consumers spend the most time physically looking at (Burke, 2005). When a shopper's location can be mapped to a cash register at the time and point of purchase, dwell and path data can be matched to sales data to provide an even fuller profile of consumer behavior.

Uniting In-Store and Out-of-Store Behavior

Retailers are also interested in understanding relationships between what customers do outside retail stores and what they do inside them. For instance, retailers are interested in knowing whether a shopper comes to a physical store, looks at products, and then purchases that or a similar product online (on that retailer's website or elsewhere). In the retail industry, this approach is often called an *omnichannel engagement strategy*: It involves engaging with and gathering data about consumers across multiple sites and platforms to create a "seamless experience" for sales (NetSuite, Inc., 2015, p. 8). By having access to out-of-store customer data, retailers can train in-store sales associates to leverage such data for targeted upselling (NetSuite, Inc., 2015).

Mechanisms of Worker Control

We identify four mechanisms through which companies draw on customer-derived data and marshal emerging technologies to restructure managerial practices to workers' potential disadvantage. The four mechanisms are summarized in Table 1, and are described in more detail below.

Table 1. Mechanisms of Worker Control.

Consumer data	Managerial practice	Effect on worker
Traffic	Scheduling optimization	Instability + unpredictability
Customer in-store interactions + behaviors	Persistent + particularized evaluation	Control + greater capacity for differentiation between workers
Customer profile (clienteling information, customer identity, shopping history, preferences and attitudes)	Knowledge externalization + interaction standardization	Substitutability
Traffic + customer in-store interactions + customer profile + direct customer input	Automation (self-service)	Replacement

First, we explore how firms channel customer data into systems for making granular and dynamic demand forecasts. These forecasts allow firms to optimize their scheduling decisions, resulting in unstable and unpredictable schedules for workers. Second, tracking data about customers' in-store behavior—particularly their interactions with store associates—provides new bases for particularized and persistent evaluation of workers. Third, workers are made more substitutable, as clienteling technologies induce workers to externalize knowledge about customers that might otherwise have remained locked away inside their heads, hence reducing their value to the firm. And finally, the use of sensor data facilitates greater self-service by customers, risking that employees' jobs will be replaced altogether by automated systems.

Dynamic Scheduling

In an effort to optimize staffing, many retailers have begun to use algorithmic scheduling software, marketed by companies such as Kronos, Shiftboard, and Workplace. These algorithms draw from a variety of data sources (Skorupa, 2012), including dynamic, fine-grained data about customers, such as purchase histories and in-store behavior, to forecast traffic and sales levels.

Labor costs are often the largest operating expense under managers' control (Workforce Insight, 2012, p. 3), and employers have a strong interest in efficiently allocating staff. A poor match between the number of employees on the floor and the amount of customer traffic can be detrimental in two directions: Staff too few employees during a period, and sales may suffer (as customers become frustrated with long lines, difficulty getting assistance, and the like); staff too many, and unnecessary labor costs can cut into profit margins. The goal for store managers is to closely and dynamically forecast and optimize staffing needs: Schedule enough staff to run the store and service customers effectively, but reduce excess labor costs to the greatest extent possible.

Traditionally, demand has been operationalized (and staff scheduled) based on aggregate store sales during a given period. But sales volume is an imperfect indicator: Peak traffic periods may differ

from peak sales periods (Retail Info Systems News, 2016), and sales figures represent only transactions that were completed, not transactions that might have been completed if staff had been better aligned to consumer demand. Consider scenarios in which potential customer demand might not be captured by sales data, but might be used to drive worker scheduling: Customers may have been unable to get staff assistance with a complex purchase, may not have been “upsold” on additional or premium purchases by a nearby sales associate, or may have given up on a purchase after seeing long lines at the register. Focusing on customer traffic helps to account for potential demand by more closely tracking when customers are in the store, who they are, where they spend time, and how frequently their visits to the store are converted into sales (Workforce Insight, 2012). As one industry white paper describes, “Retailers making smart use of [traffic and customer interaction data] may be able to achieve the rare feat of simultaneously lowering labor costs and raising conversion rates” (Retail Info Systems News, 2012, p. 5). Analytics derived from customer interaction data can be used to set staffing levels, generally, and to ensure that the best-performing associates are at work during high-traffic periods (Retail Info Systems News, 2016)—or to assign particular employees expected to perform well in different circumstances. For instance, “one sales associate might flourish with longer customer engagements during periods of low traffic, while another might be a star at multi-tasking and boosting conversion during times of high traffic” (Workforce Insight, 2012, p. 4).

Data-driven staffing algorithms, however, facilitate a variety of “just-in-time” scheduling practices that can contribute to the precarity and instability of low-wage workers’ lives.² Retail employees have long had to deal with irregular and unpredictable schedules—working different hours each day, different days each week, or an unpredictable number of hours each month, often with little advance notice. Advances in the software systems used to create store schedules may exacerbate these dynamics, as retailers demand greater flexibility from their employees in response to more dynamic forecasting of staffing needs.

First, because projections of customer demand are more granular (i.e., able to project demand on a more detailed and incremental scale; for instance, in 15-minute rather than one-hour chunks; Retail Info Systems News, 2012; Skorupa, 2012), workers may be scheduled to work shorter shifts or in “split” shifts on a single day (i.e., clock in for a high-demand period, clock out for a slower period, and clock in again when the store gets busy a few hours later). Whereas such an arrangement saves on labor costs for the employer, it can still effectively occupy a worker’s time for the entire day, denying her the opportunity to engage in paid work elsewhere.

Second, because projections may be more finely tuned to the variability of demand over time, a worker’s number of hours may fluctuate significantly and unpredictably from week to week. Unpredictable and highly fluctuating schedules make income levels precarious, make childcare arrangements contingent, and can prevent workers from holding down multiple jobs or attending night classes.

² Just-in-time scheduling borrows from a logic that has a long history in manufacturing, in which a move toward just-in-time production introduced new modes of worker surveillance and control (Sewell & Wilkinson, 1992).

A third set of problems arises because demand forecasts are more temporally dynamic: Schedules can be adjusted at short notice (or in real time) in response to new factors or updated forecasts. As a result, workers may receive very little notice of their work schedules, and previously scheduled shifts may be subject to greater risk of modification or cancellation. Another widespread practice is the use of call-in shifts, in which workers are required to be available “on call” for a shift on a given day (but with no guarantee of getting a shift, and no payment for their required availability). In 2015, the use of call-in shifts at retailers such as Urban Outfitters, Victoria’s Secret, and J. Crew occasioned a large class-action lawsuit in California and a broad investigation by the New York Attorney General based on allegations that the practice amounted to wage theft (Maheshwari & Lewis, 2015; Tabuchi, 2015). In one study, approximately 30% of service-sector workers reported that their employer used on-call shift scheduling, and 49% of these workers reported that they rarely ended up working during an on-call shift (Schwartz, Wasser, Gillard, & Paarlberg, 2015). Some companies go even further, requiring workers to be physically “at hand” but not officially clocked in to a shift until authorized by the scheduling algorithm. In 2014, three lawsuits brought by McDonald’s workers claimed that managers required workers to show up to work and wait—unpaid—to clock in until the management software determined that enough customers were in the store to meet a given employee-to-sales ratio; or, after a shift had begun, to clock out if business was slow and wait around until it picked up (Greenhouse, 2014). The foodservice industry’s attempt to deal with fluctuating foot traffic resembles what retailers have begun to do in their stores, with similar effects on workers.

Taken together, these effects can have demonstrably negative, destabilizing impacts on workers’ social and economic livelihoods. The negative economic impacts of nonstandard work schedules have been well documented (and, notably, are borne disproportionately by women and people of color). Unpredictable work patterns are linked to outcomes that include higher worker stress, greater work–family strain, and interference with nonwork activities (Henly & Lamber, 2010; Henly, Shaefer, & Waxman, 2006). Many workers report fear of retaliation or threat of job loss if they complain about scheduling; women reported this threat at five times the rate of men (Schwartz et al., 2015). These harms can extend intergenerationally. Research has demonstrated that the children of parents with unpredictable work schedules suffer cognitively and behaviorally (Morsy & Rothstein, 2015).

The economic effect of these scheduling practices, then, is to use customer-derived data to externalize risk associated with fluctuations in traffic from the firm onto workers. Less responsive systems for allocating staff—for instance, systems in which employees worked a fixed and regular schedule regardless of unexpected dips in demand—meant that firms bore more of the costs of excess capacity (in the form of workers’ hourly wages). Retailers have long attempted to displace risk onto workers, including by way of commission, which allows firms to pay workers a nominal hourly wage and limit additional pay to occasions when workers make sales. If few customers come into a store, workers have fewer opportunities to make commissions and retailers avoid having to pay for unnecessary work. More granular, variable, and dynamic scheduling practices—driven by the collection and analysis of customer data—displace even more of these costs onto workers.

Granular Evaluation and Management

The same mechanisms that allow retailers to track customers' in-store behavior can also create new opportunities for more granular evaluation and management of workers. By piggybacking on systems developed initially to monitor customers' movements, retailers can track how associates move around the store over the course of a shift, when they interact with customers, and whether those encounters are converted into sales.

Retailers have long struggled to develop effective ways to measure staff performance, and frequently enlist customers in the assessment of workers. In stores where staff work on commission, customers are routinely asked during checkout whether they received help from anyone. Retailers may assess daily sales in relation to total customer traffic, but recognize that such ratios can be misleading, in part because traffic counters may not be able to differentiate between customers and staff. Even commonplace activities such as workers' breaks, involving frequent exit and reentry, can compromise daily figures.

Reliable accounts of customers' in-store behavior require retailers to develop ways to identify—so as to exclude—staff in their observations of retail floor activity. Vendors have developed a variety of mechanisms to perform "exclusion detection." Certain companies issue badges to staff that include Bluetooth beacons, which signal to the relevant sensors that they should ignore people wearing these devices. Wi-Fi-based tracking systems register when a person on the floor is carrying a phone known to belong to an employee and then remove records keyed to these identifiers from data sets that document customer behavior. Still others rely on machine vision to recognize the unique characteristics of staff in video footage and exclude them accordingly (Retail Info Systems News, 2012).

Ironically, the need to exclude workers from these counts became an opportunity to include employee evaluation as part of vendors' offerings. In many cases, companies that set out to develop more effective customer-tracking technologies later began offering services focused on employee evaluation, including analyses that could be much more granular (worker-specific, in many cases) than those they would replace. Although touting the ability to exclude retail staff from customer traffic analyses, vendors increasingly also emphasize how effectively they can monitor workers and the interaction between shoppers and staff (Shaw, n.d.).

Recognizing when customers are physically proximate to staff can reveal many useful details to a manager. As Kronos's director of retail notes, "while traditional people counters are frequently integrated with forecasting, video counters can also help evaluate the employee/customer engagement" (Retail Info Systems News, 2012, p. 4). Such data document where in the store an encounter took place and how long the customer and associate engaged one another, suggesting whether the engagement may have influenced the customer's subsequent purchase. They create a much more exhaustive account of the relative contribution of individual staff members to a given purchase. Sales associates who might have been evaluated as a team (based, say, on aggregate sales) or as individuals (based on intermittent or impromptu observations by managers) can now be assessed on the basis of fine-grained, particularized, persistent scrutiny. Systems that observe interactions between customers and staff reduce uncertainty

about the perceived relative value of each staff member. A narrow focus on worker monitoring in retail settings would miss that much of workers' experience on the job is now informed by what retailers can learn about customers and their interactions with staff.

Even when interactions between associates and shoppers do not translate into sales, retail technology promises a way to assess the quality and effect of the encounter. In line with the introduction of voice analysis to call centers (Jones, 2015) and the adoption of sentiment analysis (Kennedy, 2016), vendors can now provide brick-and-mortar retailers with the ability to assess the emotions of customers as they navigate through the store and engage with products and staff. Integrating emotion detection into the analysis of video footage can help retailers understand the affective states of customers and staff before, during, and after their encounter, with the expectation that visible changes in customers' emotions can be attributed to staff. In this way, retailers may look to customers' emotional responses to evaluate workers' performance, even when customers do not buy an item.

Of course, vendors also emphasize that these same data can help improve workers' performance, not just measure it. Managers can leverage these data to reduce associates' idle time, assign them to the tasks that they are best suited to perform, and orchestrate associate-customer encounters that seem likely to be profitable. For example, Amazon recently patented a system that can identify when a customer in a physical store is using its Wi-Fi network to comparison-shop on a competitor's website. When such activity is detected, the system integrates that information with other customer data—including the customer's estimated value to the retailer and her location in the store—and might direct a sales associate to assist the customer. Amazon's patent suggests that this might occur through "a message . . . communicated to a sales representative[s] device," which might include "identified information associated with the consumer [including] name of the consumer, consumer account information with the retailer, a desired item, . . . a location of the consumer, etc." (Ward, 2017, p. 10). In so doing, retailers can use customer data to steer encounters with staff members, who may further draw on the data in interacting with the customer (see Figure 3).

According to Kronos's director of retail, tools of this sort "ensure a preferred associate is in the right place at the right time to convert a customer" (i.e., to a sale; Retail Info Systems News, 2012, p. 4). At the extreme, vendors promise to help retailers match staff to customers and to furnish staff with a strategy and script that will prove most effective with specific customers (Aislelabs, n.d.). In these situations, the retailer draws both on what it knows about the customer and also, potentially, what it knows about the staff member's likelihood of turning encounters with people of this sort into sales. Data-driven matching of customers to workers is an increasingly common managerial tactic in call centers (Lebowitz, 2015); these tools aim to reshape retail work along similar lines. The capacity to collect data about customers' in-store behaviors, movements, and encounters operates as a basis on which retailers can direct workers' tasks and persistently evaluate their performance, demonstrating that observation of one group can facilitate control over another. However, the refractive dynamic in such cases can be complex because retailers may rely on observations of both customers and workers to make management decisions. Refractive surveillance may well take place alongside, and work in concert with, surveillance in which observation and control are more directly coupled.

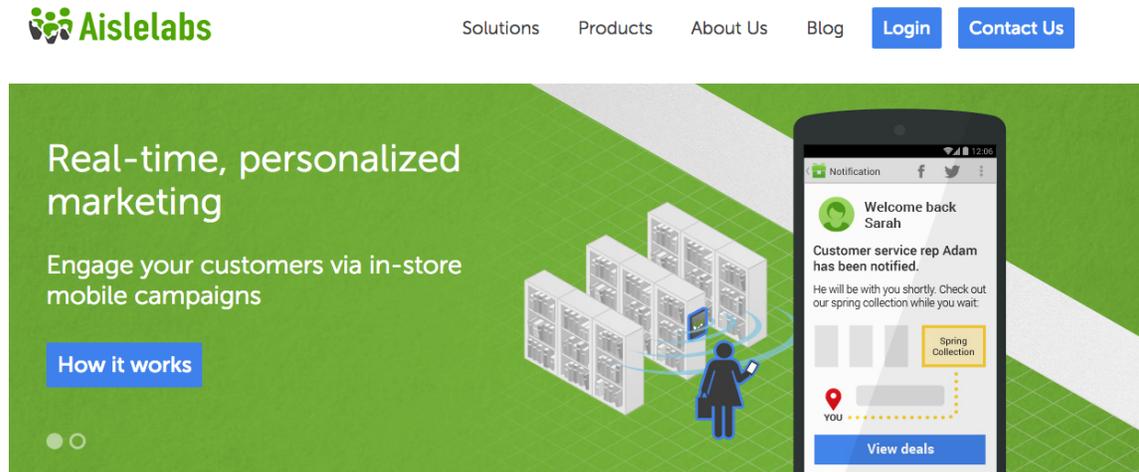


Figure 3. AisleLabs sends notifications to the phones of customers who have opted into the retailer's program. The unique identifier from Sarah's phone allows AisleLabs to identify her and direct specific salespeople to help (AisleLabs, n.d.).

Clienteling

In some retail environments (particularly higher-end retailers), store associates sustain personal relationships with their customers over time. An associate may maintain a personal "book of business," a list of clients with whom she has repeated contact, and about whom she has developed specialized knowledge regarding preferences, sizes, purchase history, and other characteristics. These customers may specifically seek out that associate for personalized service when they shop at that store. Practices of cultivating these personal relationships are known as *clienteling* (Rhodus, 2015; Richter, 2014).

These practices can include maintaining personal contact with the customer, encouraging them to come into the store, providing special access and promotions, and otherwise creating a personal in-store experience. Clienteling may assist in maintaining or augmenting sales for a retailer, but it also may provide advantages to sales associates. Depending on the retailer's compensation structure, associates may earn commissions based on clienteling practices; beyond this, personal relationships with customers make workers more valuable to the firm because their knowledge about specific customers may be hard to glean from other sources. As one vendor of clienteling software warns,

retailers are going to wake up and see that their associates are building a Rolodex of information that is outside of their corporate systems, and that they will need to create linkages from those worlds back into the retailer's world. Otherwise, they risk . . . associate[s] going down the road to their competitor and taking those customers with [them]. (Retail Info Systems News, 2013, p. 5)

Increasingly, data-driven technologies threaten the value of workers' internalized knowledge. This can happen in two ways. First, firms have more information about their customers from data sources other than their in-store interactions with staff, and can use these data to personalize customer service and promotions, potentially reducing the added value of clienteling practices as a whole. And second, the practice of clienteling is changing. New clienteling technologies make customer data available to staff across the store, often on mobile devices (Speer, 2015), and associates may be required to input customer information into these digital systems rather than keeping it in personal records or in their own heads. This operates to externalize workers' knowledge about customers.

As an illustration, consider the women's apparel retailer Chico's, known for fostering long-term personal relationships between store associates and their customers:

Frequent Chico's shoppers are regularly recognized when they enter their local store and associates are encouraged to provide a personalized, memorable experience based on previous interaction with clients. . . . [I]t has been a long-standing tradition at Chico's for sales staff to keep paper-based customer books. Associates record notes on customer purchases, style preferences, and anecdotal information on the reason behind a shopper's visit, and leverage those notes to increase sales and create a tailored, engaging experience on return visits. . . . Each associate kept his/her own book, meaning that all of those customer insights were not available across the enterprise, greatly reducing its potential impact. (Denman, 2015, para. 5-7)

The clienteling practices imagined by vendors of data-driven retail technology to support sales staff sound remarkably similar:

Associates using tablet devices, for example, can identify a particular customer by his or her loyalty card number or other identifying data, such as an e-mail address or phone number. With a clienteling solution, the associate now has data such as the individual's purchase history, her overall value to the retailer across multiple channels, and her responses to recent promotional efforts. An associate in an apparel store can draw on her knowledge of what's already in the customer's closet at home, recommending items in similar styles or from the same designers. The associate can also assemble an outfit using both previously purchased items and prospective purchases, and use the tablet's screen to show how items will work together. (Retail Info Systems News, 2013, pp. 4-6)

There is one crucial difference here: Whereas customer information resided with one specific Chico's sales associate, clienteling software makes that information available to any associate.

Chico's itself has developed an app-based clienteling solution that merges the unstructured data provided by store associates with "the large amounts of CRM [customer relationship management] information the brands are constantly collecting to provide associates with an even more powerful selling and customer engagement tool" (Denman, 2015, para. 8). The cloud-based app centralizes all of the information Chico's has about customers and makes it accessible across the entire enterprise (Denman,

2015). The company is currently developing a feature that will allow store managers to reassign associates' "Love Lists" (books of business) to a new associate should the associate leave Chico's, "ensuring shoppers continue to receive the personalized interactions to which they have grown accustomed" (Denman, 2015, para. 13). Although this feature is designed to maintain consistency in customer interactions, it also makes workers more readily substitutable for each other, reducing their individual value to the employer. A well-established book of business is a less advantageous bargaining chip for an individual associate—say, in negotiating pay or work conditions—when any associate can access detailed customer data. In this way, the collection of information about consumers may weaken workers' job security.

Clienteling software can also reduce the value of those skills traditionally associated with a capable salesperson: the ability to recognize a lucrative repeat customer or read a new shopper and marshal relevant persuasive techniques. In vendors' imagined future, retail technology that automatically identifies high-value customers as they enter the store and alerts staff will improve salespeople's efficiency and efficacy (Skorupa, 2015), rendering their jobs more fulfilling as well. But systems that match staff to customers and recommend sales scripts and strategies routinize the affective labor of retail work, in line with longstanding trends toward the standardization and close management of associates' customer service interactions (Ikeler, 2016). Such a shift does not suggest that retailers no longer value information about customers' preferences; rather, they are leveraging data sources other than sales associates' knowledge to learn about and cater to such preferences. Using technologies such as these, salespeople become human vehicles for a data-driven persuasive strategy, not workers prized for their sales instincts or experience. In this regard, retail-tracking technologies may empower less experienced retail staff by undermining the value of their more experienced colleagues, effectively reducing the bargaining power of retail staff as a whole. This might seem like a familiar case of labor deskilling, whereby workers' honed craft gives way to a system that encodes much of that knowledge in more formal procedures or tools designed to automate much of the process. Note, however, that workers' deskilling in this case depends on the ability to learn not just about the way workers execute tasks, but also the way customers behave: These are time and motion studies of customers as much as workers.

Self-Service

Self-service technologies are a well-established part of the retail environment, particularly at supermarkets and drugstores, where self-checkout machines are increasingly common. These devices replace human cashiers with a mix of sensors and visual interfaces, enlisting customers in the process of identifying the items in their shopping carts, handling payment, and bagging goods. Unlike standard cases of technological unemployment (Levy & Murnane, 2012), self-service technologies in retail have tended to displace some part of the labor previously performed by staff onto customers.

However, although previous technologies have enlisted customers to partially replace workers, new technologies use customer data toward this end. So-called "digital signage"—special (often touch-sensitive) screens connected to a computer and frequently accompanied by a camera and other sensors—can react dynamically to customers as they make their way through the store. Customers can interact directly with the signs by pressing on the screen or gesturing to the camera, but the signs may react

independently to the mere presence of customers, collecting data about passersby. Computer vision, for example, can help to ascertain the gender, race, age, or emotional state of shoppers. Retailers might even rely on facial recognition to identify customers, or simply check for the unique identifiers from phones in the nearby area. By establishing the identity of customers, retailers can bring to bear all they know about these specific shoppers in personalizing signage. Advances in customer monitoring and computation may make it possible for in-store signs to outperform even seasoned salespeople in catering to the precise interest and preferences of customers, and possibly even replace them entirely.

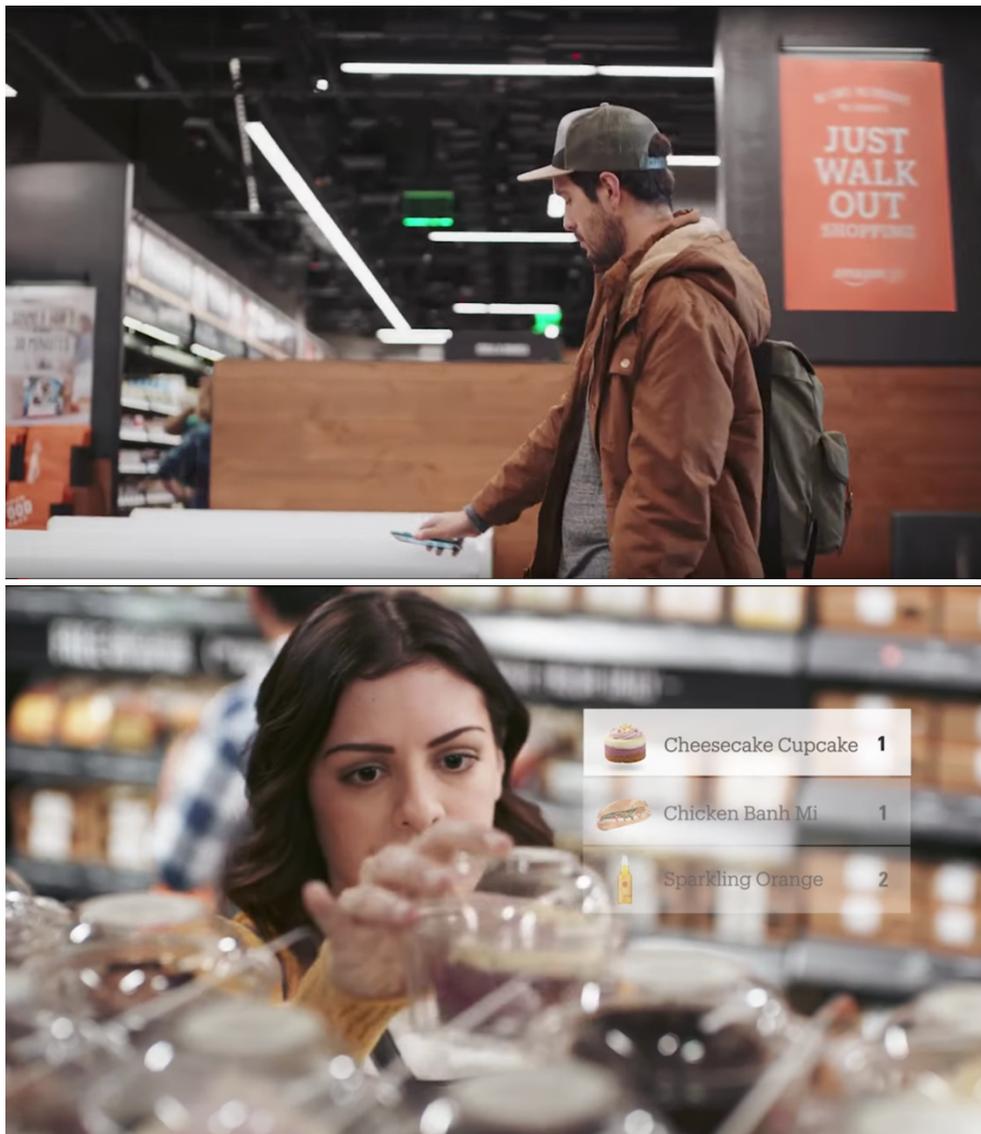


Figure 4. Scenes from promotional video demonstrating the Amazon Go store (Amazon, 2016)

The recently announced Amazon Go is the purest expression of a future of retail in which sensors in the built environment and the sense-making of machine learning render customer interactions with staff completely unnecessary (Amazon, 2016). In a promotional video, Amazon depicts a convenience store where customers use an app on their smartphones to identify themselves as they enter the store (see Figure 4). Sensors and computer vision allow Amazon to track each person as he or she strolls the aisles and to identify the specific items that customers take from the shelf. This allows the company to maintain a running list of the items in consumers' carts, and allows customers to simply walk out of the store without having to stop to ring up their purchases. Amazon charges customers' accounts automatically using what the company calls "just walk out" technology. In the nearly two-minute clip, the only employees that appear are either stocking shelves or preparing food. At no point do customers interact with staff—or even acknowledge their presence. The workers that remain in Amazon Go are there to fill and maintain the store, not to service customers directly, and this is only possible because Amazon can identify customers and track their every action. With sufficiently intense and sophisticated customer monitoring, certain workers are no longer necessary.

Refractive Surveillance in Practice

The consequences of customer data collection on workers' economic outcomes are unlikely to be uniform across managerial contexts; the aim of our analysis here has been to demonstrate how these technologies open new avenues through which customer data collection may be leveraged for managerial control. Our analysis has focused on the plausible uses of nascent technological and managerial systems rather than empirical assessment of the extent to which such systems are currently implemented on the ground. In practice, the effects of these systems are likely to be heavily contingent on formal and informal corporate policies, compensation structures, local conditions (including legal constraints), and acts of resistance on the part of workers or managers. Organizational technologies and information systems are never deterministic: Their effects are moderated by extant organizational structures (Barley, 1986; Kelley, 1990), social roles and networks (Barley, 1990), and other local conditions within a workplace (Jonsson, Holmstrom, & Lyytinen, 2009). Further research should investigate what precise economic outcomes result for workers on the basis of these managerial tools and how different contextual factors moderate those effects.

External influences will also shape the frameworks within which firms operate. Legal constraints on firm behavior—particularly those designed to protect workers' interests—may mitigate the economic impacts of data-driven managerial practices: For instance, several states and localities have considered or passed bills that would require workers to be paid for call-in shifts (DePillis, 2015). Public pressure also instigated some changes in the use of scheduling software on the part of both employers and vendors. Starbucks reformed some of its scheduling practices following a critical *New York Times* article detailing their effects on workers (Kantor, 2014). Kronos, the scheduling software vendor, added a plugin to give managers more insight into the stability and equity of workers' schedules as a result of negative media reports (O'Donovan, 2015). Other vendors have begun to explicitly integrate workers' concerns (Workjam, 2016), often by increasing workers' capacity to edit unworkable schedules (Bernstein, Kesavan, & Staats, 2014). These changes highlight the possibility that, in some contexts, these technologies might be used to advance workers' interests. Scheduling software could be used to optimize labor schedules to create

greater predictability for workers. Even when customer data help retailers make more efficient use of their staff (e.g., by reducing the total number of hours worked), the remaining workers might still benefit from new technologies if cost savings are passed along to them in the form of higher wages. Other tools could give associates actionable information about customers that might augment their capacity to make sales, which, if they are paid on commission, might benefit specific workers economically, even as it makes the labor force as a whole more fungible (Barocas & Levy, 2016).

In addition, consumers might resist the implementation of technologies that collect data about them in retail settings in the interest of protecting their personal privacy. Should customer resistance be sufficiently strong—such that a substantial number of consumers avoid specific stores, opt out of data collection, or engage in public protest—retailers might hesitate to adopt certain data collection technologies. The effects of consumer privacy on workers' interests are equivocal, depending on whether customer data are marshaled in a way that empowers or undermines workers. Consumer privacy could actually impede workers' interests if managerial systems are implemented in a way that allows workers to benefit from the value extracted from customers' data, whereas customers' privacy interests might align with workers' concerns if the systems that surveil customers also operate to disadvantage workers.

Conclusion

Refractive surveillance broadens the scope of analysis of data collection to more comprehensively account for its effects on populations other than its putative target. In the retail context, customer data collection has the capacity to reshape managerial practices—to the potential economic detriment of workers—via several independent mechanisms. Customer traffic data allow retailers to optimize labor scheduling dynamically, creating the potential for destabilizing and unpredictable work schedules. Customers' behaviors and interactions in stores give rise to the capacity for greater control over workers' encounters with them, as well as new forms of worker evaluation. Clienteling software externalizes customer profiles and preferences to render workers more easily substitutable; sensor-based self-service allows for workers to be replaced altogether by data-driven signage and checkout systems. Each case demonstrates refractive surveillance dynamics, in which retailers leverage customer data in the management of workers.

The refractive framework might be fruitfully applied to the analysis of a number of other data collection systems. For instance, the effects of state surveillance in the context of policing and criminal justice are commonly conceptualized in terms of how they enable state control over targets themselves (e.g., arrestees), but the very same surveillance facilitates state control over third parties, such as the family members of arrestees (Goffman, 2009) and police officers (in their role as state employees; Brayne, forthcoming). In education, academic performance data collected about students are marshaled for the management and evaluation of teachers. Parents' fitness is often evaluated on the basis of data collected from their children—learning outcomes, health metrics, and the like. Medical institutions are commonly assessed on the basis of data about patients' health. Indeed, the refractive dynamic is found frequently across social and institutional domains—perhaps whenever the evaluation of one party depends on the behavior or characteristics of another.

When considering activities that seem to threaten someone's privacy, we need to attend to those other than the ostensible focus of surveillance. In many cases, the person most deeply affected by surveillance might be another party altogether. Refractive surveillance reveals that the effects of surveillance on different populations should not be considered in isolation; to do so obscures the many, often indirect ways surveillance affects people's lives and livelihoods.

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