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How artificial intelligence will affect the future of retailing☆

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Abstract

Artificial intelligence (AI) will substantially impact retailing. Building on past research and from interviews with senior managers, we examine how senior retailing managers should think about adopting AI, involving factors such as the extent to which an AI application is customer-facing, the amount of value creation, whether the AI application is online, and extent of ethics concerns. In addition, we highlight that the near-term impact of AI on retailing may not be as pronounced as the popular press might suggest, and also that AI is likely to be more effective if it focuses on augmenting (rather than replacing) managers' judgments. Finally, while press coverage typically involves customer-facing AI applications, we highlight that a lot of value can be obtained by adopting non-customer-facing applications. Overall, we remain very optimistic as regards the impact of AI on retailing. Finally, we lay out a research agenda and also outline implications for practice.

Keywords: Artificial intelligence; Retailing; Ethics; Privacy; Bias

The retail industry is one of the most important sectors in the US. In 2018, the US retail industry generated sales of about $5.3 Trillion (Amadeo 2020). The retail industry includes giants like Walmart, Kroger, Home Depot, Walgreens and Amazon, as also includes a wide variety of online retailers, retail stores, and other retailing formats.

Very broadly speaking, retailers like (say) Home Depot can increase their profits in one (or more) of three ways. That is, retailers can increase in-store sales, and/ or increase online sales, and/ or improve the efficiency of their supply chain. As such, many retailers are excited about artificial intelligence (AI), which offers the promise to (i) increase in-store sales, (ii) increase online sales and increase potential cross-sell/ up-sell, and (iii) improve supply chain efficiency, improve in-store operations and make payments more efficient. The above point comports with Shankar (2018), who indicates that AI helps by (i) making omnichannel and mobile shopping more profitable, notably by sharpening personalized recommendations (ii) managing better the in-store experience, (iii) improving payments, customer service and CRM, and (iv) improving logistics and inventory optimization.

The influence of AI on retailing is projected to be substantial (Grewal, Roggeveen, and Nordfält 2017), for various reasons. First, retailing inherently involves contact with numerous customers, leading to the availability of customer transaction and

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Table 1
Extant academic research on impact of AI.

Article	Key point(s), as relevant to this paper	Domain
Boyd (2016)	Showed that the Facebook “emotional contagion” study resulted in ethical discussions regarding manipulation of social media content.	Marketing/ Business
Carmon et al. (2019)	Suggested that AI’s personalized recommendations may have much commercial benefits, they may cause discomfort, as some customers may perceive such recommendations as loss of autonomous choice	Marketing/ Business/ Retail
Davenport et al. (2020)	Examined the broad impact of AI on marketing.	Marketing
Edwards et al. (2014)	Showed that (some) Twitterbots may be perceived as credible, competent and attractive as humans.	Computer Science
Huang and Rust (2018)	Proposed that lower forms of AI will be good at routine tasks in simple, rule bound contexts, where the focus is on efficiency. The higher forms of AI (yet not in place) may be good at developing context-based intelligence, at being creative as regards solutions and at being able to empathize (with customers).	Marketing/ Business
Kaplan and Haenlein (2019)	Defined AI and distinguished between ANI and AGI.	Marketing/ Business
Luo et al. (2019)	Showed cases wherein customers preferred human service agents versus bots	Marketing/ Business
Mende et al. (2019)	Showed that interactions with humanoid service robots may trigger discomfort, with downstream consequences	Marketing/ Business/ Retail
Qiu and Benbasat (2009)	Showed that anthropomorphizing bots enhances social presence, enhances shoppers’ trust in the bots and increases shoppers’ bot usage intentions as a decision aid	Computer Science
Rai (2020)	Examined the tradeoff between AI explainability versus AI predictive accuracy	Marketing/ Business
Shankar (2018)	Examined how AI may reshape retailing[3]	Retailing
Syam and Sharma (2018)	Examined how AI may impact the sales function	Marketing/ Business
Wang and Kosinski (2018)	Used AI to examine facial features and predict customers’ sexual orientations	Marketing/ Business

attribution data. Second, these first-party data can be augmented with second-party data from external sources (e.g., rebate data from CPG firms partnering with the retailer) and/ or third-party data (e.g., social media or reports by data brokers such as Acxiom). When AI is used to analyze such data, it can deliver *real-time* and *personalized* recommendations, both of which are significant value drivers for retailing.

To illustrate the above, we present two exemplars. First, using smart shelf technology, retailers like Kroger seeks to deliver customized product offers and pricing to every shopper as they walk through the aisles in their local grocery store (Marr 2018). If a customer creates a shopping list on a store’s dedicated app, this app can guide them to relevant sections of the store, potentially triggering a targeted price promotion (Bandoim 2018). Second, the Canadian firm Kanetix, whose website allows prospective customers to compare the policies of numerous insurance providers, used AI to segment potential customers in specific ways to boost conversion. This effort led to a 2.3x return on investment (Davenport et al., 2020).

In addition to the above, Morgan (2018) indicates that “AI . . . greatest impact could be felt across the supply chain. From anticipating orders to managing deliveries, AI has the power to drastically increase efficiency in all areas of the supply chain. . ..” However, extant academic literature related to AI and its impact on retailing remains relatively sparse (see Table 1). As such, this paper focuses on how retailers should think about adopting AI.

Specifically, this paper proposes a framework for how senior managers in retailing firms should think about adopting AI. This framework differs from extant work on AI and/or marketing (e.g., Davenport et al. 2020; Kaplan and Haenlein 2019; Shankar 2018; Syam and Sharma 2018) in at least four ways: (i) its exclusive focus on retailing, (ii) its examination of customer-facing versus non-customer-facing AI applications, (iii) its being based on interactions/interviews with senior managers (Table 2), and (iv) its examining not only how AI should be adopted, but also the role of various moderating factors that may influence AI adoption. At the end of the paper, we propose an agenda for future research.

Artificial intelligence

In this paper, we build from Kaplan and Haenlein’s (2019, p. 17) definition of AI as “a system’s ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation.” The authors differentiate artificial narrow intelligence (ANI) from artificial general intelligence (AGI). ANI applies to specific areas (e.g., image recognition, fraud detection) and involves below human-level intelligence. In contrast, AGI can autonomously solve problems in multiple domains and may possess intelligence comparable to humans.

Most ANI applications are rule-based requiring logic and consistency (Huang and Rust, 2018). As an example, IBM’s Deep Blue used rules and “brute force” algorithms to defeat some of the top chess players. Contexts with structured data, rules, and predictable outcomes are ones in which ANI can even outperform humans, but it is less able to function in new domains. In contrast, AGI involves “learning how to learn,” and such applications can analyze non-structured data and address

[3] This paper builds from, and differs from, Shankar (2018). Key points of difference relate to its considering the differential impact of customer-facing versus non-customer-facing AI applications, and examining not only whether AI should be adopted, but also the role of various moderating factors that may influence pace of AI adoption.

Table 2
Interviews with senior managers.

All interviews were conducted by 2−3 co-authors.
Interviewees were typically emailed a few questions ahead of time, to get interviewees thinking about AI:
#1what are offline players doing with AI in stores? (we know lots about online AI applications) What are some ways AI is being used in the sales process in-the-store (facial recognition, emotion recognition, dynamic pricing et.)?
#2where will most of the near term action be? Will it be inward facing, which may be faster/ easier to execute? Will it be outward facing, which is more complicated, but may lead to more benefits? Within outward facing AI applications, will most action be related to pricing/ service/ last mile delivery, or will there also be AI applications that materially push the envelope into upfront demand creation/ origination?

	Interviewee	Key point(s) made	Select quotes
1	VP of a leading vendor offering AI solutions	-many retailers will start with non-customer-facing applications	*“often start with the stuff that is truly not really customer-facing”*
		-AI can add real value in terms of (i) which customers to target, and (ii) what should the customer offer be	
2	MD at a consulting firm, primarily consulting on AI strategy	-many have not started with AI	-*“less than 15 or 20 percent have managed to take AI beyond the lab”*
		-non-customer-facing applications are important, and can drive substantial value	-*“if you think about logistics . . . a lot of money on the table”*
		-either (AI) lets you create deeper insights using existing data/types of data, or it facilitates the collection and analysis of new data/new types of data	
3	Global AI Lead at a consulting firm	-non-customer facing applications can involve substantial value. Many will start there, as low hanging fruit	“*low hanging fruit . . . supply chain*”
4	Head of Business Development at a leading mall operator	-AI can impact in-store experiences, not just customer service, but also the actual shopping experience	*“you could put (the AI-powered robot) . . . it would tell you how to get to places within the mall, etc.”*
5	CEO of a leading vendor offering AI solutions	-clients may start by implementing relatively simple ‘assistance bots’, that help human service agents deal with inbound customer service requests, by providing scripts, by gauging customer’s tone etc. In the absence of the bot, an agent can handle 2−3 parallel conversations, but with a bot, an agent can handle many more conversations. Also, having a human service agent in between the bot and the customer reduces risk -after a successful implementation, such clients would start to enquire about, and potentially implement (more advanced, and relatively autonomous) ‘nudging bots’, which influence various stages of the customer journey	*“Some customers who are not comfortable with AI will start with [‘assistance bots’]”*

complex, idiosyncratic tasks (Huang and Rust 2018). However, it is important to clarify that AGI is not a near-term reality (Davenport et al. 2020), and AI researchers indicate only 50–50 odds of achieving AGI in the next three decades (Müller and Bostrom 2016).

Noting that ANI is likely to reflect the short term (or even the medium term) of the state of AI, we propose that retailers should look to AI applications to augment (rather than replace) human capabilities. For example, a version of vee | 24’s ‘assistance bots’ works with (human) service agents to respond to incoming customer service requests. These bots then assist service agents in various ways, e.g. (i) by analyzing a customer’s tone, and so providing the service agent greater insight into the customer interaction, (ii) by providing the service agents a suitably scripted response, which the agent can use as-is, or with modifications, and (iii) by allowing the service agent to handle a higher caseload. In effect, vee | 24’s AI augments the service agent’s capabilities. This example makes two points, highlighting (i) balancing AI and human input and (ii) that even ANI can lead to significant value.

While some retailers have adopted selected AI applications, many retailers have either not begun their AI journey or are in that journey’s early stage. A Capgemini study found that (i) over 70% of retailers had yet to use AI, and (ii) only 36% of retailers had some roadmap for AI deployment (Capgemini 2018). This very point also surfaced in our interviews with senior managers (Table 2, interview #2). Hence, in the next section, we address how retailers should develop an AI strategy and sequence their AI adoptions.

A framework for AI adoption

Given what we know about the state of AI, we now outline a framework for how retailers may develop a suitable AI strategy and think about adopting AI. The primary factor that we consider is the extent to which an AI application is ‘customer-facing.’ This paper builds on the work of Shankar (2018), which outlines two main ways in which AI can impact retailing: (i) demand-side applications (e.g., personalization/ recommendation systems, customer relationship management, in-store customer experience management, payment management), and (ii) supply-side applications (e.g., inventory optimization, logistics, store payout optimization).

We note that more demand-side applications are of the customer-facing variety, rather than non-customer-facing. Examples of in-store customer-facing applications include (i) Softbank's Pepper, who directly engages with in-store customers, assisting with customer service (also see Table 2, interview #4), and (ii) Amazon Go, which uses AI to manage automated check-out processes. Examples of online customer-facing AI applications include vee | 24's 'nudging bots,' which suitably interact with (and guide/ 'nudge') online shoppers during their online customer journeys, and Alexa — an Amazon voice assistant, typically located in customers' homes — which interacts with customers primarily via voice and is increasingly used for online shopping.

In contrast, an example of an in-store non-customer-facing application is the in-store robot Tally (used in Giant Eagle stores, as discussed above), which minimally interacts with customers (other than avoiding running into them). Furthermore, there are a set of applications used by (online and store-based) retailers in managing their supply chain (e.g., Carrefour uses SAS Viya/ ML to support demand forecasting — Leonard 2019), which also reflects relatively non-customer-facing applications.

As the examples above show, the customer-facing determination is not dichotomous but instead reflects a continuum, with AI applications differing in the extent to which they are customer-facing. At one end of the continuum, nudging bots are very substantially customer-facing as they interact directly with the customer. At the other end of the continuum, non-customer facing AI applications do not interact much (or at all) with customers, as in the example of the Tally robot or Carrefour's SAS Viya. In between are AI applications like assistance bots that listen to customer conversations but do not directly interact with customers.

How may retailers choose to adopt AI applications? Based on our discussions with senior managers (Table 2, interview #5), we argue that retailers choose to balance risk and return. The return relates to increased commercial benefits, whereas the risk relates to implementation risk (relating to technology and data) and the associated risk that any AI glitch may negatively impact customer relationships. Building on this point, the CEO of an AI vendor firm (Table 2, interview #5) indicated that her clients might often start by implementing AI-powered assistance bots that help human service agents deal with inbound customer service requests. However, after a successful implementation of assistance bots, such clients may inquire about and potentially implement AI-powered nudging bots, which directly interact with online shoppers and influence various customer journeys. Customer journey management is one of the most central aspects of moving consumers from awareness to conversion, as well as getting them to consider different merchandise and service options (Grewal and Roggeveen 2020; Puccinelli et al. 2009; Grewal, Levy, and Kumar, 2009), therefore, such AI-powered nudge bots can be invaluable.

The argument here is that assistance bots do not interface directly with the customer, and so even if there is a glitch or error, the human service agents can intervene and smooth over the problem. Hence the risk associated with assistance bots is somewhat less. The CEO of the AI vendor firm went on to indicate that only after such (non-customer-facing) implementations (in this case, involving a version of assistance bots) are successful, are retailing firms more confident about implementing customer-facing applications (nudging bots). Note here that the risk associated with nudging bots is higher, as any glitch directly (and negatively) impacts customers. Therefore, consistent with sentiments expressed by various senior managers we interviewed (Table 2, interviews #1, #3, and #5), as the first element of our framework, we predict that retailers are more likely to adopt non-customer-facing AI applications (versus customer-facing AI applications) (**P**$_1$).

Key variables that are likely to moderate this relationship

Nevertheless, it is not clear that retailers will always prioritize adopting non-customer-facing applications. Many factors may impact when an AI application is adopted, and we make three predictions below.

Application value

McKinsey & Company projects that - across 19 industries - AI will have the most value impact in the retailing sector (Chui et al. 2018). This value impact is expected to be driven by various factors. First, retailers frequently 'interact' with many customers, leading to retailers having vast amounts of first-party customer data (both, transaction data and/ or attribute data). Second, these first-party data can be augmented with second-party data from retailer-linked sources (e.g., rebate data from firms partnering with the retailer) and/ or third-party data (from sources unrelated to the retailer e.g., social media data and/ or reports by data brokers such as Acxiom and Datalogix). When AI is used to analyze the sum totality of such (very rich) data, some AI applications may have the ability to deliver high-value predictions and recommendations.

To the extent an AI application has exceptional value potential, retailers may take the view that the opportunity is well worth the risks, and so such an AI application it may be adopted by the retailer sooner than later. This implies that if a customer-facing application and a non-customer-facing application have similar value, the non-customer-facing application may be adopted first (consistent with P$_1$). However, to the extent that a customer-facing application offers the promise of exceptional value, it may be adopted relatively sooner, despite the risks involved.

We predict that the adoption of AI applications is moderated by the AI application's value potential. Retailers are more likely to adopt non-customer-facing AI applications (versus customer-facing AI applications), but less so when the AI application has substantial value potential (**P**$_2$).

Online versus in-store

Many AI applications straddle both online and in-store settings. For example, Behr (paints) has an AI application that suggests paint color recommendations based on customer reactions to various colors. Such recommendations create much value; Behr estimates that use of this application leads to 8.5% increase in subsequent retail store visits (Singeetham 2019).

Nevertheless, for the purposes of this discussion, we contrast AI applications that operate primarily in online settings versus those applications that operate in-store. This point involves some nuance. For the purposes of this paper, we argue that a customer logging into an AI-driven retailer 'app' at home would be classified as using the application in an 'online setting' AI application, whereas if same customer is inside the retail store and gets a text reminder from the same 'app', then this would be an 'in-store' AI application.

Inside a retail store, there is more significant potential for customer discomfort. As an example of this, assume that the customer is shopping using the Target app. If the setting is an online setting, the customer may not find it strange if the Target website reminds the customer of prior purchases and prior likes and dislikes. However, inside a retail store, the customer has expectations of privacy (vis-à-vis the Target app). Those walking past a Target store or those merely browsing in a Target store would not ordinarily expect Target to know who (exactly) they are. Such customers may feel discomfort if they get a reminder (via the Target app, or via a text from Target) while walking past a Target store or merely browsing in a Target retail store.[1] And this discomfort may get exacerbated if (say) the customer is with another person when this reminder is received, and/ or the reminder is about a sensitive product. Further, interactions with certain in-store AI applications - like robots – can also lead to various forms of discomfort (Mende et al. 2019; Mire 2020). These points are less relevant to relatively non-customer-facing AI applications, because in case of these applications the discomfort issue is less relevant.

When we talk about the adoption of artificial intelligence in retailing, the prediction is that non-customer-facing applications are more likely to be adopted than customer-facing ones. This is irrespective of whether the application is an 'online setting' or 'in-store' application. Within the category of customer-facing AI applications, adoption by retailers will depend on their online/ in-store status. Retailers are more likely to adopt 'online setting' AI applications because they know that online customers have fewer privacy concerns, and perceive AI applications as less intrusive into the sales process. In contrast, retailers are less likely to adopt 'in-store' AI applications because — in retail store settings — such AI applications may be associated with more customer discomfort. Such customer discomfort maps onto both operational risks (perceived breach of privacy) and psychological risks (perception threat to identity, which incorporates an element of someone who can choose to be private). To the extent that the in-store AI application has a physical form, there may also be an element of physical risk. Like Giant Eagle's use of Tally robots to scan its shelves, Walmart used Bossa Nova robots to scan its shelves. Very recently however, Walmart ceased using Bossa Nova robots, and part of this decision may have been related to customers' concerns when encountering a robot (Munster and Stokman 2020).

Accordingly, we predict that the adoption of AI applications is moderated by whether the AI application setting is online versus in-store. Retailers are more likely to adopt non-customer-facing AI applications (versus customer-facing AI applications), and more so when the AI application involves an 'in-store' application ($\mathbf{P}_3$).

Ethics

Ethics is a complex construct involving several sub-constructs (sub-issues). The first dimension relates to customer safety, and specifically, data privacy. A second dimension relates to the potential for bias. A third dimension is linked to the appropriateness of the application. Below, we deal with each in turn.

Concerns about data privacy. Regarding privacy, there are two points to consider. First, is the data 'identifiable'? Of course, a customer is completely identifiable if the customer data include their facial photo, full name, or credit card number. But, in some cases, the combination of a customer's age, gender, ethnicity, and zip code may be unique enough to trace it to a specific person. Second, how sensitive is the data? For example, data on breath fresheners arouses fewer privacy concerns than does data on political and other beliefs, or data on sensitive purchases (e.g., pornographic material, certain medications), or data that is indicative of presence in specific locations (e.g., purchase of breath fresheners in a red-light district). We suggest that both the identifiability and sensitivity of customer data are likely to be higher with AI applications. Consider, for example, attempts to classify consumers by personal traits — all of these may fall under the purview of sensitive data. Such classification attempts are more accurate if the retailer makes use of AI, and so customers' privacy concerns may well be heightened.[2]

Another perspective on AI-related privacy concerns came from a senior manager we interviewed, who indicated that AI either lets you create deeper insights using existing data/types of data, or facilitates the collection and analysis of new data/new types of data (Table 2, interview #2). Consider when AI is used to create deep insights from existing data, e.g., using customers' transaction data to generate a likelihood that the customer will get divorced (Nasir et al. 2017). Such uses of AI heighten privacy concerns because, at the time of giving up transaction data to the firm, customers would not have been able to, a priori, predict that it may be possible to use AI and glean such sensitive information. These concerns also tie back into data protection laws which require that personal data be "collected for specified. . .purposes and not. . . in a manner. . .incompatible with those purposes" (GDPR (2020), Art. 5, 1(b)).

[1] Of course, this point may vary by application. For example, AI-supported relatively autonomous payment systems may involve less discomfort, both in-store and online.

[2] We clarify that privacy concerns may still obtain, even if retailers fully comply with the laws like GDPR (General Data Protection Regulation, instituted in the EU) and CCPA (California Consumer Protection Act). This is because even if retailers comply with the law, (i) data breaches might still occur, and (ii) internal parties can still leak data (∼19% of leaks in the retail industry were by internal actors, Verizon 2019).

Consider next when AI is used to create insights from new forms of data. For example, the FaceX AI application identifies customers' emotional state (e.g., happy versus sad) and then suggests optimal messaging. The concern here is that, to the extent customers may not be aware of such data collection types, they may perceive such data collection types as intrusive and inappropriate, heightening privacy concerns.

In general, though, all the above privacy concerns should be substantially reduced in non-customer-facing AI applications (as here the retailer controls the AI application and wholly owns the underlying data and the insights). Thus, the impact of privacy concerns may primarily relate to AI applications that are more customer-facing. The general conclusion is that — especially for customer-facing applications — heightened privacy concerns may make it less likely that the retailer will adopt the AI application.

As an aside, we note that it is not always clear whether retailers should implement strong data privacy protocols. On the one hand, weak privacy protections likely diminish the extent to which customers trust retailers (Kumar and Reinartz 2018), threaten financial losses (Romanosky, Hoffman, and Acquisti 2014), and risk brand devaluations (Martin, Borah, and Palmatier 2017). On the other hand, strong privacy protections may diminish data quality and could potentially decrease retail profitability (due to a coarser match between advertisements and customer preferences). Each retailer must make this tradeoff separately, using a customized cost-benefit analysis (Abowd and Schmutte 2019).

Concerns about bias. Bias is a real concern (De Bruyn et al., 2020). To the extent that AI 'learns' from prior datasets, it may 'learn' along lines that impute particular bias. For example, even if race or gender is not a formal input into an AI algorithm, an AI application may impute race/gender from other data (e.g. location data) and use this to 'price' higher to specific demographics. At a minimum, this may have public relations costs, with other costs (e.g., loss of valuable business) also possible. For example, the Apple credit card offered smaller lines of credit to women (versus men) despite not using gender in their algorithm (but other variables used may have been correlated with gender), but no one from Apple could offer a suitable explanation for this (Wiltz 2019). This point was widely reported in the press, and led to negative public relations.

The above point — especially the public relations aspect — impacts customer-facing AI applications more, and heightened bias concerns may make it less likely that the retailer may adopt such applications. The general conclusion is that — especially for customer-facing applications — bias concerns will reduce the likelihood of adopting AI applications.

Concerns about 'appropriateness.' This point relates to concerns in AI applications that are 100% legal, and yet may spark controversy and lead to negative public relations. For example, retailers are increasing using AI to monitor facial expressions and so track mood of in-store customers (Lewis 2019). In turn, retailers use this mood data as inputs for in-store advertising and/ or in-store personalized pricing. Customers have expressed – in general – concerns about such mood-identifying AI applications (Pisani 2019), with such concerns especially heightened amongst older customers (Lewis 2019). Pam Dixon – of the World Privacy Forum – indicated that "*creepy factor here is definitely 10 out of 10*" and that retailers may use such mood information to – for example – push certain medications to those customers who are perceived as looking 'sad' (Pisani 2019). The critical question is whether such applications are appropriate enough to explore and implement; broad knowledge of such types of AI applications can lead to public relations challenges.

Other types of AI applications may also raise 'appropriateness' concerns. For example, retailers can use AI to segment their customers, wherein that they might consider overt signals (e.g., facial features, names, prior purchases) to infer whether customers are likely to be considering a divorce or potentially suffering from mental health issues. Such details can be beneficial from a segmentation standpoint. For example, if a consumer is headed for divorce, they may develop new consumption habits, require additional products and services, exhibit new brand preferences, or reallocate personal budgets and expenditures (Komaiko 2012). However, some may argue that this type of relationship information seems so personal that retailers should not try to infer it. This point is based on Target's (pre-AI) experience, which used demographics and purchase data to infer the likelihood that female customers were pregnant (i.e., a pregnancy condition score; Hill 2012), a move that, though not illegal, prompted substantial customer pushback (Fernandez-Lamela 2014). Another firm, which could infer via AI whether certain customers had mental health issues, chose not to pursue this route after its senior managers realized the potential for a public relations backlash (Burkhardt, Hohn, and Wigley, 2019).

Also, firms vary in terms of disclosure levels. A recently passed California law, SB 1001, requires retailers to disclose whether (outbound) sales calls to customers come from a person or a bot (Eisert 2018). However, this law does not specify whether similar disclosures are necessary when retailers respond to (inbound) customer queries or service requests. Because customers tend to prefer human service agents over bots (Luo et al. 2019), retailers might prefer to hide bot identities. To the extent that there is doubt if firms are masking whether the customers are interacting with a bot or human, this point may exacerbate appropriateness concerns.

Finally, retailers often set up A/B tests, to test which AI algorithms work better than others. To the extent that these tests are run without customers being aware they were part of an A/B test, this may also exacerbate appropriateness concerns. This point builds on an instance from the pre-AI period, when there was much outrage when customers learned that Facebook had manipulated content to view the downstream effect on subsequent posts (Boyd 2016).

This point — about AI appropriateness and potential public relations fallout — impacts customer-facing applications more. The general conclusion is that, especially for customer-facing applications, appropriateness concerns may reduce the likelihood of adopting AI applications. This point, however, is less applicable to those AI applications which are relatively non-customer-facing.

Across all the discussions regarding privacy, bias, and appropriateness — or more broadly, ethics — the following point

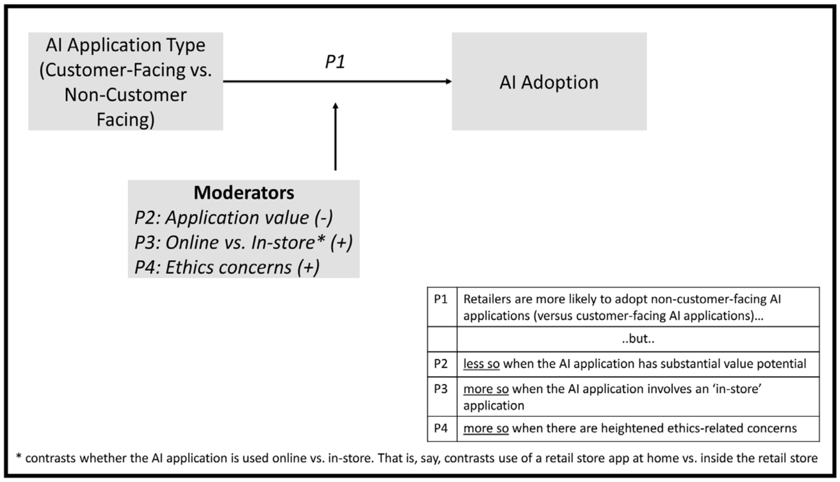

Fig. 1. Framework for AI Adoption.

emerges. Especially for (some) customer-facing applications, heightened ethics concerns, and consequent negative public relations concerns, may reduce the likelihood of adopting AI applications. Put another way, heightened ethics concerns may increase the likelihood of adoption of non-customer-facing applications (as for non-customer-facing applications, ethics concerns are less likely to apply).

Therefore, we predict that the adoption of AI applications is moderated by ethics-related concerns. Retailers are more likely to adopt non-customer-facing AI applications (versus customer-facing AI applications), and more so when there are heightened ethics-related concerns ($\mathbf{P}_4$).

In Fig. 1, we put together all the above predictions and portray the prediction framework outlined in this paper.

Agenda for future research

Our proposed research agenda (Table 3) builds off the AI adoption framework we developed. We focus on three areas: customer-facing AI applications, online versus in-store, and ethics concerns. In contrast, we do not focus on non-customer-facing applications and application value. Given that the retailer controls most aspects of non-customer-facing AI applications, the adoption of such AI applications appears relatively straightforward. Also, application value is a somewhat straightforward concept and so is not explored further.

Customer-facing versus non-customer-facing applications

Unintended consequences of AI. It may be interesting to examine the unintended consequences of AI on customer behavior (also suggested in Shankar 2018). The prevailing wisdom is that using AI to better predict what customers want should be positively perceived, reducing customer search costs. However, are there unintended consequences of customers knowing that an AI application has profound insights into their behaviors? In this context, the key factors may well be to what extent perceived autonomy is valued by customers in such AI-mediated settings (André et al. 2018), and to what extent customers perceive AI as servants or partners. The product type might also be pertinent. After all, perceived autonomy tends to be more relevant for hedonic products, due to stronger links to customers' identities. Such research may be important. To the extent customers perceive a threat to their perceived autonomy, they may make subsequent choices that depart from prior choices (or depart from choices proposed by the AI algorithm), which may be essential in AI applications. Testing these points may lead to useful contributions.

It may also be useful to examine AI-powered augmented reality (AR) and virtual reality (VR) applications. AR and VR allow consumers to 'experience' products without physically touching them. The ongoing COVID-19 pandemic made in-store shopping relatively unsafe. In response, retailers are looking to improve their sales efforts online, so AI-powered AR and VR have attracted much interest. For example, shoe companies could use such technologies to (virtually) give customers an idea of how their shoes could perform (e.g. Nike Fit). In 2020, the Japanese online fashion retailer Zozo launched Zozosuit 2, a polka dot bodysuit which helps customers take very precise clothing measurements, without necessarily going into the store. The Zozosuit 2 value proposition is evident in this statement: *"…accurate and easy-to-use body measuring technology has become a holy grail for online fashion retailers trying to reduce returns. The industry has been boosted by consumers shopping at home during the COVID-19 pandemic…"* (Nussey 2020).

Future research could ask whether these technologies accomplish this goal and whether (and when) such technologies have the potential to overstate and/or mislead and — as an unintended consequence — may increase customer discomfort. It may be noted that the initial AI-powered Zozosuit was unsuccessful ("…*failed experiment*… *suit was not accurate*") and led to negative downstream consequences, including Zozo quitting Europe (Fox 2019).

Bots. AI-powered bots are popular AI applications. Thus, academic research on bots is an important area. In the field of marketing and information systems, past research has found that in some cases, customers tend to prefer human service agents over bots (Luo et al. 2019), but not in others (e.g., the case of

Table 3
Agenda for Future Research.

Topic	Research questions	Methods/ Data
Customer-facing versus non-customer-facing applications	-are there unintended consequences of AI on customer behavior? Are there downsides if customers know that a retailer's AI application has deep insights into their specific customer behavior? Are there trait factors / state factors that influence such downsides?	Qualitative interviews A/B testing/ lab studies
	-what factors may influence discomfort with bots/ robots? What may be the role of accents and dialects? Are there trait factors that influence such discomfort (e.g., extent to which AI is perceived as servant)?	Qualitative interviews A/B testing/ lab studies/ field studies
	-how may AI capture and use customers' non-overt responses?	A/B testing/ lab studies. Methods from psychology and the biological sciences (using devices like neurotransmitters etc.)
	- how to make the most optimal use of AR/ VR? Also, may such technologies overstate and/ or mislead and – as an unintended consequence – increase customer discomfort? -how best to link AI applications to AR/ VR applications, to sell to online shoppers along the full customer journey (*links also to online vs. in-store*)	A/B testing/ lab studies/ field studies/empirical methods. Requires expertise relating to facial and other imaging, AR etc., which then needs to be integrated with domain expertise.
	-when interacting with voice assistants, do voice characteristics (e.g. paralinguistic cues like vocal pitch and vocal intensity) and quality of the underlying 'AI' (e.g., conversational ability) impact customers' attitudes (e.g. perceived satisfaction) and behavioral intentions?	A/B testing/ lab studies/ field studies/empirical methods
	-how should manufacturers deal with voice assistant 'shopping channels' like Alexa, as in time it is possible that voice assistants (like Alexa and Google Home) may control a substantial portion of online search and online shopping?	Qualitative interviews/ A/B testing
Online versus In-store	-in hybrid shopping formats (online shopping, curbside pick-up), there is a rich research opportunity relating to predictive analytics relating to this shopping format.	Empirical methods, A/B testing. Also requires not only customer data and store data, but also new types of data relating to factors like weather data, traffic data, work hour data etc.
	-how to better improve the capabilities of AI applications to create/ respond to social media posts? How do customers react to social media posts that are AI-generated?	Qualitative interviews, A/B testing/ lab studies/ field studies
	-can AI-generated reviews might be helpful in cases where there is a dearth of online reviews (or, where there are so many reviews that a consumer can't make sense of them)? How might such AI reviews be created, and what are downstream implications? What are downstream implications of knowing that AI-generated reviews are virtually indistinguishable from regular reviews?	Empirical methods, Qualitative interviews, A/B testing/ lab studies/ field studies
	-are there other (better) ways for customers to get an idea of how garments look on them (without necessarily changing into such garments), perhaps using AI-powered holograms and other such technology?	Empirical methods, Qualitative interviews, A/B testing/ lab studies/ field studies
Ethics-related concerns	Safety/ privacy concerns: -Schneider et al. (2018) describe a method for retailers to alter transaction data to establish insightful pricing models but simultaneously protect customer privacy. Zhou et al. (2020) describe a method to alter facial data to establish desired inferences but simultaneously prevent customer identification. Future research can identify different ways to manage privacy but still enable retailers to collect and examine data using AI to draw insights.	Empirical methods (requires suitable data, like in Schneider et al., 2018)
	-Customers balance their privacy concerns against the increased benefits of personalized offers (e.g. Carmon et al., 2019). Researchers thus might continue to investigate how customers view this trade-off, as well as how their individual difference or state variables might affect this view, in order to inform their choices.	Qualitative interviews, A/B testing/ lab studies/ field studies
	Bias concerns: -would making AI more explainable, even at some performance cost, reduce bias perceptions? When may making AI explainable be more valuable?	Empirical methods, Qualitative interviews, A/B testing/ lab studies/ field studies
	- how to identify bias in relatively nascent AI applications, before much harm is caused.	Empirical methods, A/B testing/ field studies
	Appropriateness concerns: -it would be useful to examine new ways to think about appropriateness considerations. University IRBs offer a good model for regulating academic research; retailers that conduct similar research, such as with A/B testing, might consider something "IRB-like"?	Qualitative interviews

Twitterbots; Edwards et al. 2014). Furthermore, anthropomorphizing bots enhances social presence and shoppers' trust in the bots and increases shoppers' intentions to use the bot as a decision aid (Qiu and Benbasat 2009).

A close cousin of bots are robots, with the latter having an accompanying physical form. Noting that robots incorporate some level of AI, there has also been research into how individuals respond to robots. Beyond work relating to the uncanny valley, this work has found that service by robots can lead to perceptions of discomfort, with downstream consequences (Mende et al. 2019), and that the 'gender' of the robot moderates perceived discomfort levels. Future work can look at areas more directly related to retailing. For example, beyond gender, what other elements may influence discomfort levels with bots? There has been limited research into the benefits of bot/ service robots with accents or dialects. There has also been limited research into traits/ individual differences that impact discomfort levels, e.g., the extent to which bots/ service robots are perceived as servants.

Another cousin of bots and robots are AI-powered voice assistants (e.g. Amazon Alexa, Google Home). These voice assistants perform a wide variety of functions, ranging from delivering information (e.g. weather information), controlling home devices, improving productivity (e.g. via alarms, calendars), shopping etc. Such devices are present in ∼100 million homes, and household penetration is expected to double by 2024 (Tankovska 2020). There are at least two important research streams relating to voice assistants. The first relates to the nature of voice interactions with such assistants (Bressgott et al. 2020); both characteristics of the voice (e.g. paralinguistic cues like vocal pitch and vocal intensity) and quality of the underlying 'AI' (e.g., conversational ability) may impact customers' attitudes (e.g. perceived satisfaction) and behavioral intentions. The second relates to how manufacturers choose to deal with 'shopping channels' like Alexa, as in time it is possible that voice assistants (like Alexa and Google Home) may control a substantial portion of online search and online shopping. For example, in Australia, Woolworths set up integration with Google Home (Parentich 2020); this has parallels to the 'store-within-a-store' concept, wherein manufacturers rent out space in retail stores. How manufacturers may choose to deal with voice assistants, is a fascinating area for future research.

In the days ahead, the role of bots will increase in importance, not only for customer service but also for guiding shoppers in their customer journey. Hence retailers and academics need to understand factors that may reduce discomfort associated with bots and make bots more effective.

Examination of non-overt responses. It may also be useful to research how, in retail settings, AI applications may be linked to non-overtly expressed consumer responses (e.g., rise in skin temperature, eye gaze). Uniqlo is experimenting with AI-powered UMood kiosks wherein customers are shown products, and their (non-overt) responses are elicited via neurotransmitters (Morgan 2019). After that, such neurotransmitter inputs are used to generate product recommendations. Such technologies are in their infancy but offer much promise. Useful research in these areas must by definition be multidisciplinary, including not only marketing researchers but also researchers from other disciplines like psychology and the biological sciences. Non-overt responses may be especially useful in understanding latent preferences.

Online versus in-store

Retail stores were negatively impacted during COVID-19. In response, many retailers have substantially improved their online operations, transitioning either to pure online operations or to a hybrid model wherein customers buy online but then pick up at retail locations. Even post COVID-19, the incidence of buying online is likely to sustain, and remain considerable. The challenge for retailers will be to implement customer-facing AI applications that function in online settings are as effective as in-store selling efforts.

Also, research efforts can examine how best to link AI applications to artificial reality (AR)/virtual reality (VR) applications, to sell to online shoppers. Moriarty (2020) suggests that linking AR to AI can help reduce product returns relating to household goods, as customers can view the goods in an AR visualization of their home prior-to-purchase. Rayome (2018) points out that cosmetics retailers, like Sephora, use AI-enabled AR applications to replicate in-store sales efforts. Sephora's Virtual Artist is an AR application that allows customers to 'virtually' use cosmetic products, and then use digital beauty tutorials to achieve various styles. The Color Match feature allows the customer to upload a photo and find the right skin tone color shades. Academics and practitioners can more broadly investigate how combining AR and AI can play a role along the full customer journey, and impact a broader category of product categories.

Much has been written about how AI will improve predictive models for online shopping (Agrawal, Gans, and Goldfarb 2018). These expected improvements stem from the exponential growth of computing power, an exponential decline in data storage costs, and the existence of vast quantities of data on consumers and their shopping habits. In the future, we will observe the addition of data stemming from the rise of not only online shopping, but also hybrid shopping formats, involving (say) online ordering and curbside pickup (Repko 2020). In such a scenario, predictive models powered by AI can examine not only customer data and store data, but also new types of data relating to factors like weather, traffic, and work hours.

Over the recent years, a lot for research has started to emerge regarding how retailers can create a social presence in the online social media space (Herhausen et al. 2020), and how they should go about addressing posts by consumers (Herhausen et al. 2019, Ordenes et al. 2017, 2019) and reviews by consumers (Motyka et al. 2018). AI enabled social media solutions are starting to play an important role (Kaput 2019). For example, Hubspot can create (drafts of) social media posts, and the AI-powered application 'Socialbakers' helps with advanced audience insights (e.g. which social media influencers best map onto the target audience). Future research can look at two issues. The first is how to further enhance the capabilities of AI applications to create / respond to social media posts. The second is to examine downstream implications, relating to how customers react to social media posts that are AI-generated. For example, noting here that customers do – in some cases – react negatively to chatbots (Luo et al. 2019), it may well be that customers react negatively to social media posts that they perceive as AI-generated.

Future research can also examine the relationship between AI and online reviews, especially identifying fake reviews generated by AI systems. In general, there is some concern that AI-written reviews are indistinguishable from reviews written by individuals (Tousignant 2017). In this sphere, there are two specific paths that future research can pursue. On a more positive note, can AI-generated reviews be helpful in cases where there is a dearth of online reviews (or where there are so many reviews that a consumer cannot make sense of them)? How might such AI reviews be created, and what are the downstream implications? On a more negative note, what are the downstream implications of customers knowing that AI-generated reviews are virtually indistinguishable from regular reviews?

While much of the AI impact is expected in online retailing, AI is also expected to augment in-store sales. Neiman Marcus is looking to install 'MemoryMirrors' (memorymirror.com), a digital mirror that allows customers to virtually 'try on' clothes (without actually doing so) (Dove 2015). Further, the MemoryMirror allows for capture of a wide variety of still and video clips, which can be sent to customers' friends etc. for their opinion. Not only does the MemoryMirror improve the in-store customer experience, but also retailer can collect a wide variety of data that can help in various ways. Such AI-powered mirrors improve sales, as customers can get an idea about how garments look on them, without having to actually change into such garments. Future research can look to improve this, perhaps using AI-powered holograms and other such technology, to develop other (better) ways for customers to get an idea of how garments look on them, without necessarily changing into such garments.

Ethics-related concerns

We next pivot to ethics-related issues, considering (in order) issues relating to privacy, bias, and 'appropriateness.'

Privacy. Schneider et al. (2018) describe a method for retailers to alter their transaction data to establish insightful pricing models and protect customer privacy. In brief, these researchers show that retailers can use synthetic data to replace private data but still maintain the relationships within pricing models. Further, other related work (Zhou, Lu, and Ding 2020) has explored how to transform facial images to 'contour-as-face' images, to remove demographic inferences for identification (such as age and gender) while still preserving the ability to identify inferences such as emotion. Future research should continue along these lines, to identify different ways to manage privacy and yet enable retailers to use AI and draw insights. Such research should expand to alternative data formats, such as textual data from AI chatbots, facial images from store cameras, geolocation data from retailers' apps, and voice data from customers' interactions with firms. For example, how can a retailer ensure that data from an AI chatbot is suitably anonymized, such that the data is not identifiable and sensitive to a particular consumer, and yet in a format that can be analyzed to reveal deep insights.

Also relevant is research that relates to the privacy-personalization tradeoff (Davenport et al. 2020; also see Aguirre et al. 2015). Benefits of personalized offers (e.g., Carmon et al. 2019) are balanced relative to privacy concerns. Researchers thus might continue to investigate how customers view this trade-off, and how individual difference variables or state variables might moderate this tradeoff. Such research may inform retailers regarding tradeoffs when designing AI applications, e.g. while offering very personalized offerings, how intrusive can retailers be when seeking personal information. For example, Cuthbertson (2019) argues that Alexa should not be allowed in bedrooms as, despite its convenience and personalization benefits (e.g., for obtaining information, controlling devices, ordering), Alexa's placement in the bedroom has privacy costs (as Alexa is 'always on').

Bias. We also urge more research into 'explainable' AI, which may reduce the potential for bias. If the AI is relatively more inexplicable (i.e., more 'black box'), customers are less likely to trust it, which hinders adoption. Such explanations are not legally mandated (cf. banking, where explainability is required), but recommendations and actions may be more likely to be perceived as 'unbiased' if a 'black box' explanation is also provided (Rai 2020). Initiatives for more explainable AI relate to either 'opening' the AI black box (see Ribeiro, Singh, and Guestrin 2016; Štrumbelj and Kononenko 2014), or else using (somewhat) less accurate statistical methods or data. Retailers should examine both approaches to better understand when one or the other (or neither) may be more appropriate. This point is non-trivial for retailers, especially if they wish to avoid negative public relations of the type associated with (say) the Apple credit card offering credit lines which (prima facie) appeared to be contingent on gender (as discussed above).

Using AI algorithms also raises concerns about embedded bias. While algorithmic bias can be spotted relatively easily when looking at the output of AI systems, findings its root cause is often surprisingly difficult since the mechanics of such algorithms are often a black box. AI systems tend to replicate and amplify any form of bias present in the input data. Easy steps to reduce bias, such as removing variables (e.g., about race or sex), are frequently inefficient, since the AI algorithm replaces those variables with a combination of other, correlated variables. Given that the consequences of biased algorithms can be discrimination or harm, this presents a significant risk. A straightforward, although not efficient, solution is to simply use AI systems to merely suggest decisions, which must be subsequently validated by human decision-makers. Examining how to identify bias in relatively nascent AI applications before much harm is caused is an important area for future research. In this regard, we note that researchers have already started to work on fairness-aware or fairness-embedded algorithms (Barocas, Hardt, and Narayanan 2020; Rambachan et al. 2020).

Appropriateness. Finally, it would be useful to examine new ways to manage concerns about appropriateness. University institutional review boards (IRB) offer a good model for regulating academic research; retailers that conduct similar research, such as with A/B testing, might need something "IRB-like." Boyd (2016) describes the substantial backlash Facebook

Table 4
Use Cases (AI in Retailing).

Technology	Application Description
Amazon/ Alexa	A voice assistant device, primarily used in the home, which interacts with customers primarily via voice, and is increasingly used for online shopping.
Amazon Go	Retailers use AI when automating check-out processes, such that customers simply pick up what they want without requiring any staff assistance.
Behr paint app	Customers use Behr's paint app to identify the optimal color for their painting application; includes the ability to color-match vis-à-vis uploaded photographs.
FaceX	This is a facial identification software. Retailers can use this AI to identify VIP customers who visit stores. It can also be used to target advertisements e.g. FaceX can identify the customer-type (e.g. 'young' 'female') and prompt display of suitable advertisements.
Pepper	Softbank's Pepper (robot) directly engages with customers in banks (e.g., HSBC) and retail stores (e.g., b8ta), and assists with customer service.
Kanetix	Customers visit Kanetix to examine various insurance options. AI identifies which customer are provided insurance incentives and which are not provided them.
Kroger smart shelf	Using 'smart shelf' technology, retailers (like Kroger) seeks to deliver customized product offers and pricing to every shopper as they walk through the aisles in their local grocery store. If a customer creates a shopping list on a store's dedicated app, it can guide her or him to relevant sections of the store, then potentially trigger a targeted price promotion.
MemoryMirror	Retailers like Neiman Marcus are looking to install 'MemoryMirrors', an AI-powered digital mirror that allows customers to virtually 'try on' clothes (without actually doing so). Further, the MemoryMirror allows for capture of a wide variety of still and video clips, which can be sent to customers' friends etc. for their opinion.
Tally	In Giant Eagle stores, Tally (a robot) scans on-shelf products, checks whether more of each product is held in inventory etc.
SAS Viya/ Carrefour	An AI-enabled platform, to support retailers do demand forecasting and reduce waste
UMood/ Uniqlo	The company built booths in Australia, where shoppers can step in and see various clothing options. Using neuro-headsets, their neurological responses are analyzed using AI. Based on this analysis, Uniqlo "is able to recommend the perfect" clothing option for each shopper.
vee | 24	Amongst other things, vee | 24's bots assist with customer service, and interact with (and guide/ nudge) online shoppers over the course of the customer journey.

encountered when users learned it had altered newsfeeds to conduct research experiments into their emotional reactions; perhaps an IRB-type entity could have suitably intervened in such a situation?

The idea of creating review boards is not new (see Simonite 2018). However, the recent spotlight on individual technology companies makes the issue salient and heightens its importance. As Simonite (2018) states, "*None have got it right so far. There aren't any good examples yet... purely internal processes...are hard to trust, particularly when they are opaque to outsiders and don't have an independent channel to a company's board of directors.*" Suitably setting up review boards, and making a suitable tradeoff between the flexibility to experiment versus concerns about appropriateness, are important issues for retailers seeking to adopt AI applications. It goes without saying that review boards need not only contain those with an ethics background, but also those with the technical backgrounds such that there can be a rich discussion about the tradeoff between privacy and insight.

General discussion

How AI will change the future of retailing

AI will change the future of retailing in three ways. It will improve retailers' (i) online interactions with consumers, (ii) in-store interactions with consumers, and (iii) supply chain operations. The various use cases mentioned in this paper (and listed in Table 4) illustrate this point. As mentioned above, vee | 24's nudging bots improve online interactions with customers, interacting with and (suitably) guiding online shoppers during the customer journey. Softbank's Pepper improves in-store interactions by aiding with customer service. Moreover, SAS Viya is used by retailers like Carrefour for supply chain optimization. Such AI offers substantial value potential, despite the AI of today being relatively ANI (and likely to remain ANI over the short-to- medium-term).

Nonetheless, as discussed above, many retailers are just at the start of (or, in the early stages of) their AI journey. Hence, in this paper we address how retailers should develop an AI strategy and sequence their AI adoptions.

How should retailers think of adopting AI applications

This paper develops a framework to understand how retailers may adopt AI (see Fig. 1). To do so, we build on both prior work and our own extensive interviews with senior managers. First, we differentiate customer-facing AI applications from non-customer facing AI applications. Next, we examine why AI adoption likelihood may vary, contingent on the extent to which the AI application is customer-facing (P_1). Finally, we explore why application value (P_2), whether the application is online versus in-store (P_3), and ethics concerns (P_4) may moderate the likelihood of customer-facing AI being adopted.

We also propose a research agenda, which highlights specific areas for further consideration by retailers, academia, and policy experts. We would also like to note that AI will likely have important implications for both the role and use of in-store technology (see discussion on other technologies; Grewal et al. 2020a; Grewal et al. 2020b) and how merchandise is displaced in the store (see discussion on merchandise and merchandising; Roggeveen et al. 2021).

Conclusion

In closing, we offer three cautions, as also a note of optimism. First, the short-to-medium-term impact of AI on retailing may not be as pronounced as promoted in the popular press. This is not to say that the impact of such AI will not be profitable; it may well be (and in many cases, has been). Nevertheless, it is essential to temper public expectations suitably.

Second, at least in the short term, many AI applications may involve AI augmenting (rather than replacing) employees. For example, assistance bots may help customer service agents deal with incoming customer service requests. Assistance bots can provide customer service agents with suggested response scripts, improving both response time and accuracy. Also, assistance bots can analyze customers' tone of voice, and can provide input to customer service agents about the customers' mood.

Third, whereas most of the notable stories about AI in the popular press involve customer-facing applications, value may be obtained by adopting non-customer-facing AI applications. A Capgemini study indicated that "*AI use cases... focused on operations ... most profitable... AI for procurement tasks (7.9% ROI)... and optimizing supply chain route plans (7.6% ROI)* ..." (Capgemini 2018). While the anecdotes about Carrefour using SAS Viya for supply chain optimization, or Amazon's supply chain using AI such that Amazon can offer very rapid shipping times (Selyukh 2018), may not make the public press that often, such AI applications can be, and often are, the source of substantial value.

Notwithstanding the cautions above, we remain very (very) optimistic as regards the impact of AI on retailing. As indicated prior, McKinsey has projected that AI will have the most value impact in retailing (Chui et al. 2018). Not only are retailers expected to use AI to significantly add value to supply chain operations, but also retailers can use AI to suitably analyze the significant amounts of (own, and third-party) customer data to deliver high-value recommendations. Retailers who can suitably harness the power of AI, will thrive.

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