Ann Oper Res
DOI 10.1007/s10479-016-2276-3

Big data initiatives in retail environments: Linking service process perceptions to shopping outcomes

John A. Aloysius[1] · **Hartmut Hoehle**[2] · **Soheil Goodarzi**[2] · **Viswanath Venkatesh**[2]

Abstract Given the enormous amount of data created through customers' transactions in retail stores, it comes as no surprise that retailers are actively seeking initiatives to leverage big data and offer their customers superior services that provide mutual, previously unattainable benefits. Nonetheless, fulfilment of such a strategic aim requires customers to adopt and embrace emerging technology-driven services. Exploring customers' perceptions of such big data initiatives in retail environments, we develop a model examining the effects of technology enablers and privacy concerns on critical shopping outcomes including repatronage intentions, store image, and intention to use medium in the context of recently identified service configurations. We conduct an exploratory study to understand customers' reactions toward emerging shopping scenarios and to enhance our survey instrument and then conduct an online survey (n = 442) to test our model. We found that customers' usefulness perceptions of emerging services positively affected their intentions to use medium, and that their privacy concerns about the amounts of personal information, being collected through emerging services, negatively affected their repatronage intentions and store image. We discuss the implications of our work for research and practice.

Keywords Big data initiatives · Retail stores · Emerging service processes · Technology enablers · Privacy concerns · Shopping outcomes

1 Introduction

Data science and predictive analytics are becoming increasingly important for operations and service processes, with applications ranging from forecasting (Altintas and Trick 2014) to transportation and logistics (Chen et al. 2013) to online service processes (Kou and Lou

✉ Viswanath Venkatesh
vvenkatesh@vvenkatesh.us

1 Supply Chain Management Department, University of Arkansas, Fayetteville, AR, USA

2 Information Systems Department, University of Arkansas, Fayetteville, AR, USA

Published online: 27 July 2016

2012). The potential benefits that firms attempt to realize are numerous, including enhanced sales and operations planning capabilities, improved supply chain efficiencies, ability to respond faster to changing environments, and real-time decision making capabilities (Hong and Thong 2013; Schoenherr and Speier-Pero 2015). Although the potential sources for data are numerous, a contemporary view emphasizes that firms are committed to collaborative processes with their customers (Fosso Wamba et al. 2015a) and customers are in fact partners in value co-creation with firms (Maull et al. 2012). Retailers are thus aspiring to go beyond the mere capture of customer preferences via data and retain competitive advantage by extracting notable value from big data analytics (Brown et al. 2016; Wang et al. 2016). Data and inputs to the supply chain, such as checking on-shelf availability and product visibility, are now enabled by active customer participation and through emerging technologies. Taking a customer perspective in a service supply chain (Rai and Bajwa 1997; Maull et al. 2012), retail checkout processes should begin with customers when they are ready to checkout. Mobile technology is ubiquitous and pervasive, and retailers attempt to take advantage of the prevalent availability of this technology by providing their customers with innovative mobile point-of-sale (POS) services. In this innovation, customers take the role of labor in the service supply chain (Brown 2008; Sampson and Spring 2012). Nevertheless, leveraging the wealth of information made available by innovative technologies is challenging (Thong et al. 2006; Chongwatpol 2015), and mobile POS will only be a useful source of data if customers adopt and use it. In order to promote customer adoption, retailers need to understand how customers react to emerging mobile POS innovation designs that in turn could provide benefits to retail stores and customers at the same time (Schoenherr and Speier-Pero 2015).

The recent widespread use of mobile devices, such as smartphones, is changing daily routines and activities including shopping. A study by RIS Research (2015) estimates that 90 % of Americans keep their mobile devices within three feet of them twenty four hours a day, and further, mobile devices influence at least three-fourths of purchases for 44 % of Americans. Such a considerable influence has at least two important consequences for supply chain analytics: (1) it generates an overwhelming amount of data about customers' shopping behavior and tastes, resulting from sales transactions and other data captures, such as search and social media, and (2) it affects retail stores' outcomes and supply chain processes, as a substantial number (around 33 %) of all purchases in the United States are influenced by mobile devices (RIS Research 2015). In response, retailers are attempting to facilitate customer participation and autonomy in service processes (Aloysius and Venkatesh 2013). In particular, forward-looking retail stores have realized that in order to thrive in the current competitive environment, they need the capability to turn big data into big insight (Brown et al. 2007; Goller and Hoffmann 2013) and treat their customers with a superior personalized experience. With the increasing data tsunami, big data analytics can be utilized as a driver for retailers' competitive advantage (Zhong et al. 2015) and transform the retailers' entire business processes (Fosso Wamba et al. 2015b). This can lead retailers to derive intangible benefits, such as customers' repatronage intentions and positive store image, which in turn create sustained competitive advantages for them in the era of big data. Such an approach also facilitates a demand pull, as opposed to a supply push approach[1]—what has also been termed demand chain management (Christopher and Ryals 2014). Demand chains have the dual advantages of promoting both agile and lean characteristics by enabling faster customer response and lower inventories—traditionally viewed as a tradeoff.

[1] A pull-model supply chain is one where customers' actual demands justify the entrance of products into the supply chain whereas in a push-model supply chain projected demands determine what enters the process (Houston Chronicle 2016).

Prior work on retail mobility initiatives has found mobile POS technology to be a means of deriving potential benefits for retail stores (Aloysius and Venkatesh 2013). Emerging mobile POS technologies enable retailers to collect customers' data on a large scale (i.e., tackling the volume of data), tailor real-time responses to customers (i.e., tackling the velocity of data), and manage different forms of data collected from barcode scanners, iBeacon devices, etc. (i.e., tackling the variety of data). This allows retailers to utilize customers' shopping behavior, convey real-time customized responses to them, and thus providing personalized service to customers in order to meet their needs. Therefore, the potential value of emerging mobile POS as a store innovation goes beyond convenience and labor savings.

Despite the potential benefits mentioned above, firms generally face major challenges in obtaining earnings from their deployment of emerging technologies (Chronopoulos and Siddiqui 2015). In the context of this study, of particular concern is disruptive influences that emerging mobile POS services could exert on retailers because such services fundamentally change service processes to which customers may have grown accustomed. Technological capability is not the only critical antecedent to successful technological innovation (Guan et al. 2006). If not welcomed by customers, implementation of such technological innovations could result in harmful consequences (Aloysius and Venkatesh 2013), such as lack of customers' intentions to use the technology or patronize and negative word of mouth that are harmful to retailers (Thong et al. 2002). To illustrate, business reports and anecdotal evidence suggest that customers' low adoption rates, associated with the implementation of innovative technologies and services, have often incurred significant costs to retailers (e.g., Ohkubo et al. 2005; Wirthman 2013). Studies on technology adoption have established that individuals are likely to express inertia against novel technologies (for a review see Venkatesh et al. 2003, 2012). Customers' technology perceptions are known to have substantial effects on technology outcomes. Specifically, in the context of engaging emerging technologies in retail stores, customers do not always prefer personalization services, offered through emerging technologies, due to their privacy concerns (Chellappa and Shivendu 2010). In other words, customers' privacy concerns have been shown to be a prominent inhibitor of technology adoption (Aloysius and Venkatesh 2013; Venkatesh et al. 2017) that could in turn have detrimental effects on retail stores. It is thus incumbent on the retail industry to weigh the benefits of innovative POS service processes against their associated costs.

Our literature review suggests that little research has been conducted to study the potential outcomes of the employment of emerging mobile POS service processes in retail stores, and perhaps more importantly, the extant work on this area suffers from the lack of a holistic view about the underlying logic that links such technologies to their outcomes. As an illustration, although Aloysius et al. (2016) provide insights into the distinct technological designs of mobile POS services and customers' preference for those different configurations, they shed limited light on the nomological network of customers' perceptions regarding the different mobile POS services. Customers' technology perceptions are of paramount importance as they determine whether or not the innovation in question will be successfully accepted (Venkatesh et al. 2012). In other words, the innovation will only be successful and lead to sustained benefits, such as repatronage intentions and positive image, if customers have favorable perceptions about it, and thus adopting the innovative technology. Against this backdrop, we attempt to address the following research questions:

RQ1. What are the facilitating and inhibiting characteristics of emerging service processes in retail stores?
RQ2. How do these characteristics influence critical customer outcomes?

To address these questions, in the current work, we aim to grasp the effect of different designs of mobile POS technologies on customers' perceptions of emerging services and consequently, on critical outcomes that are beyond the immediate benefits and costs of selling products in retail stores. To this end, we develop a model that examines the effect of technology enablers and privacy concerns on shopping outcomes (i.e., repatronage intentions, store image, and intention to use medium). As discussed later in detail, we evaluate our model under four major, recently identified emerging in-store service scenarios (Aloysius et al. 2016) in terms of customers' perceptions and intentions. To test our model, we first conducted an exploratory study to enhance our understanding of customers' reactions to the emerging shopping scenarios and improve our survey instruments, and then, we carried out a scenario based online survey.

Our work is expected to make two key contributions. First, we extend our understanding of technology infrastructure (i.e., emerging mobile POS) that supports big data initiatives and its subsequent effect on operations and service processes. Specifically, we theorize about the adoption and use of big data-enabled service processes from a customer perspective, and consequently, the gains or losses that retailers can experience by implementing such service designs. Second, our findings about the impact of different emerging mobile POS services on the outcomes of innovative technology have important implications for practice about the emerging service scenarios that are most likely to be perceived favorably by customers, and therefore, are plausible to increase retailers' benefits of implementation of big data initiatives in their operations.

2 Background

2.1 Mobile POS characteristics

A checkout process at a retail store typically involves two subprocesses that correspond to the time and place in which a retail transaction is completed (Aloysius et al. 2016): (1) a scanning process that is a data capture of the products a customer wishes to purchase, and (2) a payment process in which the customer tenders payment for the purchase. Mobile POS disrupts traditional retail service processes because scanning and/or payment service can happen at any location in the store, and not necessarily at a designated location such as cash register. Thus, emerging service scenarios have two dimensions, i.e., scanning and payment, each of which has two modes, i.e., fixed and mobile. Under fixed scanning condition, customers scan the products in which they are interested at a fixed POS. However, customers can scan the products on the sales floor while they are exploring the aisles under mobile scanning scenario. Similarly, under fixed check out condition, checkout is done at a fixed POS. Nevertheless, check out is carried out on the sales floor under mobile checkout scenario. In our study, these four emerging in-store service scenarios (Aloysius et al. 2016) are central features of the service process (i.e., mobile POS) characteristics.

2.2 Technology enablers

Over the past decades, a vast body of research has been conducted on adoption and diffusion of technology and technology enablers. This research stream has originated from roots in social psychology to explain the antecedents to individuals' behavioral intentions. Among several models theorizing about individuals' usage behavior of emerging information technologies, usefulness and ease of use have consistently been corroborated to be the strongest predictors of behavioral intention (see Venkatesh et al. 2003, 2012). As noted by Venkatesh and Bala (2008), these two determinants consistently explain about 40 % of the variance in individuals' intentions to use a technology. Due to their ability to predict an individual's intention to use a given technology, we chose usefulness and ease of use as technology enablers. Perceived usefulness is defined as the extent to which using a technology will provide benefits to individuals in performing certain activities (Venkatesh et al. 2003, 2012). Ease of use refers to the degree of ease associated with consumers' use of technology (Venkatesh et al. 2003, 2012). According to the extensively applied models of users' acceptance of technology (i.e., TAM and UTAUT), these two beliefs determine an individual's behavioral intention to use a technology that in turn, leads to one's actual behavior (Rai and Patnayakuni 1996). In the context of our study, usefulness and ease of use are of vital importance because such technology characteristics can encourage users to adopt emerging services in retail stores as there is considerable evidence that customers have a general bias against emerging technologies (Day et al. 2004).

2.2.1 Mobile POS services and technology enablers

Prior research on technology adoption has indicated that technology design characteristics are key antecedents to users' technology perceptions (Davis and Venkatesh 2004). More specifically, it is argued that design characteristics of a given technology or service can significantly determine users' perceptions of usefulness and ease of use of the technology (Wixom and Todd 2005). Further, Venkatesh and Bala (2008) suggested that technology design can positively influence users' perceptions of the usefulness and ease of use of the technology and cause users to perceive the technology as favorable. These could be due to the fact that a well-designed technology reinforces the perception that the use of the technology in question needs less effort and enhances the user's performance. Therefore, the convenience and benefits that can be derived from employing a well-designed service instill a favorable perception among customers. For example, an emerging POS technology that is designed in a mobile fashion could allow customers to easily use their own mobile devices, incorporate their browsing with their transaction, and exit the store without facing the inconvenience of locating fixed terminals and perhaps waiting in line (Aloysius and Venkatesh 2013). Such benefits and convenience clearly foster favorable customer perceptions regarding the usefulness and ease of use of the mobile POS.

2.3 Privacy concerns

The arrival of emerging technologies that enable companies to easily collect considerable amounts of data from their customers have raised some concerns over individuals' information privacy. This is a reason why practitioners and academicians have recently witnessed significant calls for research on privacy issues in the era of big data (e.g., Baesens et al. 2014). Information privacy concerns refer to "an individual's subjective views of fairness within the context of information privacy" (Malhotra et al. p. 337, 2004). Prior work on HCI studying individuals' privacy concerns has commonly considered four aspects of privacy concerns (i.e., unauthorized access, secondary use, errors, and collection) with respect to different possibilities how emerging services or technologies could compromise users' private information. Unauthorized access is defined as the extent to which an individual is concerned about his/her personal information to become readily available to unauthorized people; secondary use is the degree to which an individual is concerned about the unjustified use of his/her information for purposes other than those for which they were initially gathered; errors are defined as the degree to which an individual is concerned about the deliberate or unintentional errors that might be made in his/her personal information; and collection refers to the extent to which an individual is worried about the amount of his/her personal information being collected by data gathering entity (Smith et al. 1996).

2.3.1 Mobile POS services and privacy concerns

As mentioned above, another aspect of customers' perceptions of emerging services is their privacy concerns. Technological advances and the advent of emerging services have led to increase in, and ease of, the collection, storage, and utilization of customers' personal information by multiple parties. Prior work on applications of technology inventions that can collect customers' information have indicated that customers perceive this practice to be privacy invasive (Chellappa and Shivendu 2010; Culnan and Armstrong 1999; Pavlou 2011). For instance, in the context of our study, customers are often reluctant to use emerging technologies in their shopping trips due to their concerns that the personal information they give to the retailers could be compromised or misused (Aloysius and Venkatesh 2013). However, privacy calculus theory (Dinev and Hart 2006) and other work on individuals' information privacy concerns (e.g., Hui et al. 2007; Laufer and Wolfe 1977; Smith et al. 2011) have argued that people tend to make tradeoffs between benefits and costs of disclosing their personal information. In other words, individuals are more likely to give up some privacy for some benefits in return (Chellappa and Sin 2005; Culnan and Bies 2003; Dinev and Hart 2006; Laufer and Wolfe 1977). This is because if users clearly see benefits in situations wherein they reveal their information to retailers, they perceive such situations to be less intrusive (Laufer et al. 1974; Simmons 1965). Hence, the more beneficial are a service process characteristics, the less is its users' negative perception regarding their information privacy.

3 Research framework and propositions

We develop a framework that links the design of emerging technologies in retail stores to technology-related outcomes via customers' technology perceptions. We argue that customers' interpretations of service process characteristics develop their perceptions of the technology which in turn could lead to outcome evaluations. Our research framework is shown in Fig. 1.

As explained below in more detail, it is important to note that in our research, service process characteristics is not a construct but provides the environmental context in which the study is conducted. That is, we investigate the impact of customers' perceptions of service processes, associated with service process characteristics, on shopping outcomes. Therefore, variations of customers' perceptions across service process characteristics (i.e., fixed scan and fixed payment, fixed scan and mobile payment, mobile scan and fixed payment, and mobile scan and mobile payment) is at the center of our proposed relationships.

Before we develop our propositions, we discuss how service process characteristics (i.e., mobile/fixed scanning and mobile/fixed payment) lead to different levels of customers' per-

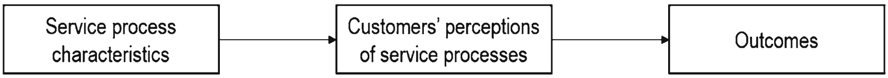

Fig. 1 Research framework

ceptions. As discussed earlier, in the context of implementing emerging technologies to service customers in retail stores, two key aspects of customers' perceptions attract a great deal of attention: (a) technology enablers, i.e., perceived usefulness and ease of use of technology (see Venkatesh and Davis 2000), and (b) privacy concerns that are inevitable by-products of emerging technologies and widely argued to exacerbate users' perceptions of the technology. Further, the emerging service process consists of two subprocesses: (a) scanning products and (b) payment, each of which could be performed in either fixed or mobile fashion. Although implementing emerging technologies to service customers appears to be a promising plan for retailers due to the associated benefits (Aloysius et al. 2016; Aloysius and Venkatesh 2013; Chronopoulos and Siddiqui 2015), retailers should take into account potential reasons that may cause such services not to be well-accepted by customers. In other words, customers accustomed to traditional shopping channels may have negative perceptions of such new technologies that could lead to negative evaluations of associated outcomes (see Ohkubo et al. 2005; Günther and Spiekermann 2005). This could incur significant costs to retail stores when investing and employing unorthodox technologies in retail stores.

A mobile technology design allows customers to browse around in different spots on a sales floor. As a result, customers are likely to perceive the benefits associated with location independent service design (i.e., mobile scanning and payment) because it could save customers some time and let them look up details about the items in which they are interested as they evaluate various products during their shopping trips (Aloysius and Venkatesh 2013). Therefore, customers may perceive more convenience in using mobile scanning and mobile payment technology design while shopping. As discussed in the literature review, such customers who perceive more benefits and convenience from employing desirable technology are likely to have higher perceptions of technology enablers and lower perceptions of privacy concerns. This is consistent with prior research having found that customers express significantly higher intention to use and lower privacy concerns for mobile unassisted technology design than other service scenarios (see Aloysius et al. 2016).

Our research model is shown in Fig. 2. Recent academic literature (e.g., Aloysius et al. 2016; Venkatesh et al. 2017) and market reports (e.g., Aloysius and Venkatesh 2013; Wirthman 2013) provide the bases for developing our research model. Specifically, latest state-of-the-art research on employment of emerging technologies in retail environments suggests that customers assisted with such technologies have positive perceptions of technology adoption (Aloysius et al. 2016; Venkatesh et al. 2017). While relishing the opportunity of using mobile shopping in retail stores, these customers express negative views regarding their security beliefs and privacy concerns (Venkatesh et al. 2017; Wirthman 2013). Therefore, we note that in order to carry out a proper evaluation of shopping outcomes, customers' positive perceptions of emerging services should be taken into account in concert with their privacy concerns related to such services. Also, as discussed later in detail, the results of our exploratory study support the reasoning behind our research model. Accordingly, based on prior work on retailing (Baker et al. 1994; Grace and O'Cass 2005), we argue that different aspects of customers' perceptions regarding usefulness and ease of use of an emerging technology as well as their privacy concerns have direct effects on their repatronage intentions, store image, and intention to use the medium.

As pointed out by Davis and Venkatesh (2004), usefulness and ease of use of a technology significantly influence a user's subsequent behavioral intentions and preferences. This linkage has been applied and contextualized in different studies and substantially corroborated over the last decade or so (e.g., Venkatesh et al. 2003, 2008; Venkatesh and Bala 2008). Therefore, applied to the context of the current research, such users' intentions and preferences include customers' intentions to return to the store and use the technology and

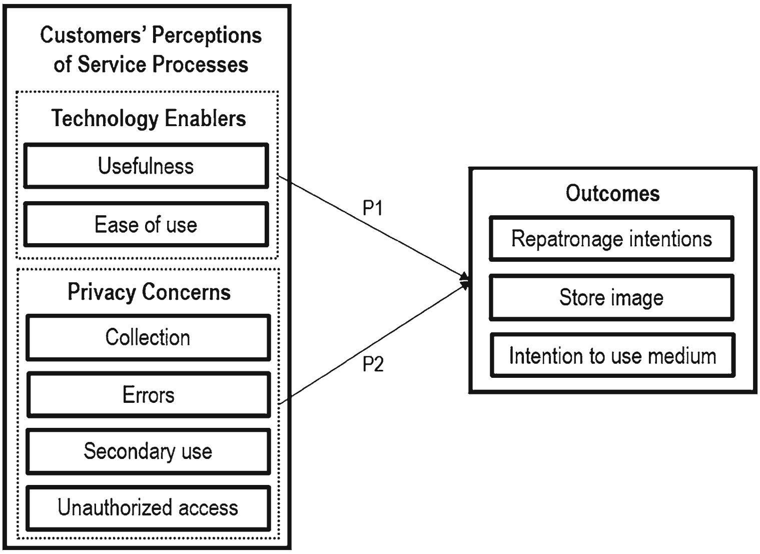

Fig. 2 Research model

to form a pleasant retail store image. Moreover, research focusing on user experiences with mobile technologies demonstrates that lower degree of usefulness and ease of use of mobile technology demotivates users to retain the technology due to the increased cognitive efforts associated with using the technology (Venkatesh and Agarwal 2006). Consequently, such cognitive overload associated with employing emerging shopping technologies, in the context of our study, results in customers' lack of intention to use the medium and patronize again, and considering the store an unpleasant place to shop.

Proposition 1 *Customers' perceptions of usefulness and ease of use of service processes will be positively associated with shopping outcomes.*

As stated earlier, the emergence of novel technologies have concerned individuals about the invasion of their privacy (Aloysius et al. 2016; Chronopoulos and Siddiqui 2015). Application of emerging services in retail stores makes customers worry about the amount of their information being collected by retailers (i.e., collection), the possibility of errors that may be made in their personal information (i.e., errors), the likelihood of misuse of their information (i.e., secondary use), and the possibility of access of unauthorized entities to their personal information (i.e., unauthorized access). For instance, Aloysius et al. (2016) found that many customers are reluctant to use mobile technologies in their shopping trips due to the potential for invasion of their privacy. Such concerns clearly pose an obstacle to customers' intentions to return to the retail store and may cause them to perceive the store to be an unpleasant place to shop. Therefore, customers' privacy concerns can reduce the benefits that retailers pursue by implementing emerging services. Further, customers' privacy concerns may cause anxiety and cognitive distrust in customers (Dinev et al. 2015) that in turn lead them to spend more cognitive effort during their shopping activities. Such an increase in customers' cognitive costs can also negatively impact customers' intentions to use the technology and revisit the store. Hence, customers' privacy concerns may also incur costs to retailers, for example, not just through losing the aforementioned customers but by the potential spread of negative word of mouth.

Proposition 2 *Customers' perceptions of privacy concerns attributed to emerging services will be negatively associated with shopping outcomes.*

4 Method

Our data collection consisted of two stages. First, we performed an exploratory study to better understand customers' reactions to our proposed emerging shopping scenarios and to modify and improve our survey instrument. Second, we conducted an online survey to evaluate customers' reactions to our four shopping scenarios and examine our propositions.

4.1 Exploratory investigation and survey improvement

To gain a thorough understanding of customers' perceptions of the emerging scenarios and to evaluate our scales for measuring customers' reactions in a large-scale survey, we first conducted store intercept surveys and followed it with focus group sessions. We carried out the store intercept surveys at three retail stores (i.e., a home improvement retailer, a general merchandise retailer, and a department store) in the southern US. After finishing with their shopping, about 200 customers voluntarily participated in our study and filled out a 10-min survey about their views on the emerging shopping scenarios. To assist the participants in understanding of our emerging shopping scenarios, we used visuals and briefly explained the emerging technologies and processes to them. The store intercept surveys were beneficial to our research for two reasons. First, we utilized the participants' feedback regarding our initial survey questions, visuals, and scenario descriptions and modified them. Second, we noticed that, in general, customers were interested in our proposed emerging shopping scenarios. As mentioned above, to better understand customers' perceptions of emerging technologies in a retail context, we also conducted two semi-structured focus group sessions, with some open-ended questions, consisting of 32 customers and 21 customers, respectively. Each focus group discussion lasted more than an hour and was conducted by one of the authors. The interviews were taped and transcribed, and subsequently coded and analyzed by the authors. Overall, the results suggested that the participants took interest in our emerging shopping scenarios and perceived them to be valuable concepts for retail stores.

4.2 Online survey

4.2.1 Participants and data collection

Our sample was drawn from the target population of a general consumer pool representing the US population. A professional research firm collected the data through an electronic survey. The research firm emailed invitations to potential respondents in the sampling frame and asked them to complete an online survey. In accordance with assurance of research compliance, the research firm had obtained informed consent from all participants before the study began. Individuals who completed the survey were given small monetary incentives by the research firm. We were not concerned about non-response bias because our sample matched the sampling frame provided by the market research firm. Further, because all responses were collected during one week and the research firm did not send out reminders to respondents, we did not deem comparing early versus late responses necessary (see Hair et al. 1998). Overall, our data consisted of 442 eligible responses. Demographic characteristics of the respondents are included in Appendix 1. The survey was designed in a scenario-based fashion—including our 4 service scenarios, and respondents were provided with contextual information and visual illustrations of each shopping scenario. An exemplary service scenario is provided in Appendix 2.

4.2.2 Measurement

To operationalize the constructs used in our research, we adapted scales from previous studies. The items and sources are shown in Table 1.

Further, to seek feedback on our questions, initial versions of our survey were circulated to industry experts. The industry experts suggested a few minor modifications—e.g., pagination—and asserted that overall the instructions were comprehensive and clear. Then, we asked two researchers who had Ph.D. degrees in business from US universities and were unfamiliar with our study to read the instructions and comment on the items and the survey structure in general. They also confirmed that the instructions were clear and straightforward.

We checked all responses for accuracy before analyzing the data. Respondents who did not correctly answer reverse-coded filler items or completed the questionnaire in less than five minutes were excluded from the initial data. Five minutes were the threshold recommended by the market research firm given our study task and the number of items in our questionnaire.

5 Results

We used partial least squares (PLS) to estimate our research model. PLS is a component-based technique that maximizes the variance explained in estimating structural models. SMART-PLS (Ringle et al. 2005) was the specific software package used for data analysis.

5.1 Measurement model

We first evaluated the psychometric properties of the scales and examined the item loadings, internal consistency reliabilities (ICRs), and average variance extracted (AVE) of the instrument used. The results suggested internal consistency and discriminant validity (Fornell and Larcker 1981; Nunnally 1978). Prior work suggests that discriminant validity is established if the inter-construct correlations are lower than the AVEs (see Tables 2, 3, 4, 5). We note that the pattern of the correlations was in line with what we proposed in our model. The measurement model validity was further supported by acceptable loadings and low cross-loadings in the model test (Hair et al. 1998). Tables 2 through 5 show the descriptive statistics and correlations for each of the scenarios (i.e., fixed scanning and fixed payment, fixed scanning and mobile payment, mobile scanning and fixed payment, and mobile scanning and mobile payment).

5.2 Structural model

Table 6 represents the results of the structural model testing. As shown in Table 6, our model provided reasonable explanatory power in understanding the outcomes, with variance explained of 59.2 %, 38.5 %, 22.2 %, and 22.6 % in repatronage intentions, 50.9 %, 25.1 %, 17.3 %, and 25.3 % in store image, and 89.6 %, 84.9 %, 80.5 %, and 83.1 % in intention to use medium for fixed scanning and fixed payment, fixed scanning and mobile payment, mobile scanning and fixed payment, and mobile scanning and mobile payment scenarios, respectively. These findings supported that our model provides a holistic view about the

Table 1 Items used to measure each construct

	Construct	Item used	Source
Technology enablers	Usefulness	I believe using mobile shopping in the store will be a useful experience	Froehle and Roth (2004)
		I believe mobile shopping in the store will add additional value to my shopping experience	
		The experience of using mobile shopping in the store will be useful to me	
		I believe that the experience of using mobile shopping in the store will add value to the overall service	
	Ease of use	I believe my interaction with mobile shopping in the store will be clear and understandable	Venkatesh et al. (2003)
		It will be easy for me to become skillful at using mobile shopping in the store	
		I would find mobile shopping easy to use in the store	
		Learning to operate mobile shopping in the store would be easy for me	
Privacy concerns	Collection	It would bother me if stores asked me to register information in order to use mobile shopping	Angst and Agarwal (2009)
		If stores asked me for information in order to use mobile shopping, I would think twice before providing it	
		I would be concerned that stores are collecting too much information about me if I use mobile shopping	
	Errors	Stores should take more steps to make sure that information related to mobile shopping in their files is accurate	
		Stores should have better procedures to correct errors in information related to mobile shopping	
		All mobile shopping related information in the store's computer database should be double-checked for accuracy—no matter how much this costs	

Table 1 continued

	Construct	Item used	Source
	Secondary use	Stores should not use information related to mobile shopping for any purpose unauthorized by individuals who provided the information	
		When people give mobile shopping related information to a company, it should never use the information for any other purpose	
		Stores should never share mobile shopping related information with other entities unless authorized by the customer who provided the information	
		The store should never sell mobile shopping related information in their computer databases to other entities	
	Unauthorized access	Computer databases that contain mobile shopping related information should be protected from unauthorized access	
		Stores should ensure that unauthorized people cannot access information related to mobile shopping	
		Stores should devote more time and effort to prevent unauthorized access to mobile shopping related information	
Outcomes	Repatronage intentions	If the store introduced mobile shopping, it is likely that I would shop at this retail store in future	Blodgett et al. (1997), Singh (1988)
		If the store introduced mobile shopping, I would not shop at this store again	
		If the store introduced mobile shopping, I would continue to shop at this store in future	
	Store image (Pleasantness)	If the store introduced mobile shopping, this store would become an unpleasant place to shop	Baker et al. (1994)
		If the store introduced mobile shopping, this store would lose its pleasant atmosphere	

Table 1 continued

Construct	Item used	Source
	If the store introduced mobile shopping, this store would become unattractive	
Intention to use medium	I would use mobile shopping to shop in the store	Froehle and Roth (2004)
	I intend to use mobile shopping the next time I see it in the store	
	I will not use mobile shopping the next time I see the system in the store	

All items were measured using a 7-point Likert-type scale (1 = strongly disagree... 7 = strongly agree)

Table 2 Reliabilities, descriptive statistic, correlations, and AVEs (fixed scanning fixed payment)

	ICR	Mean	SD	1	2	3	4	5	6	7	8	9
1. Usefulness	.971	4.683	1.667	.946								
2. Ease of use	.839	5.425	1.072	.817***	.759							
3. Collection	.885	4.791	1.463	−.583***	−.401*	.848						
4. Errors	.515	5.713	1.181	.349	.516***	−.132	.600					
5. Secondary use	.708	6.216	1.259	−.211	−.037	.380*	−.135	.650				
6. Unauthorized access	.868	6.150	1.139	−.073	.194	.337*	.105	.515**	.830			
7. Repatronage intentions	.900	4.025	1.553	.574***	.538***	−.707***	.331*	−.243	−.164	.866		
8. Store image	.960	3.525	1.895	.518**	.413**	−.674***	.176	−.241	−.052	.834***	.942	
9. Intention to use medium	.938	4.591	1.612	.936***	.826***	−.548***	.362*	−.254	−.070	.513***	.442***	.913

$n = 40$ and the square root of the AVEs are on the diagonal
* <.05; ** <.01; *** <.001

Table 3 Reliabilities, descriptive statistic, correlations, and AVEs (fixed scanning mobile payment)

	ICR	Mean	SD	1	2	3	4	5	6	7	8	9
1. Usefulness	.975	4.219	1.719	.951								
2. Ease of use	.858	5.162	1.286	.707***	.777							
3. Collection	.878	4.735	1.360	−.490***	−.365***	.840						
4. Errors	.765	5.457	1.117	−.099	.084	.239*	.727					
5. Secondary use	.898	6.268	1.128	−.038	.202	.235*	.402***	.829				
6. Unauthorized access	.856	6.329	1.031	.192	.344**	.033	.559***	.597***	.817			
7. Repatronage intentions	.884	4.004	1.393	.411***	.304***	−.576***	−.275*	−.120	−.094	.847		
8. Store image	.964	3.735	1.681	.233	.108	−.446***	−.284*	−.182	−.208	.840***	.948	
9. Intention to use medium	.951	4.052	1.702	.919***	.664***	−.492***	−.110	−.004	.176	.417**	.262	.930

$n = 82$ and the square root of the AVEs are on the diagonal
* <.05; ** <.01; *** <.001

Table 4 Reliabilities, descriptive statistic, correlations, and AVEs (mobile scanning fixed payment)

	ICR	Mean	SD	1	2	3	4	5	6	7	8	9
1. Usefulness	.951	4.402	1.388	.910								
2. Ease of use	.814	5.262	.912	.665***	.728							
3. Collection	.876	4.379	1.367	−.489***	−.412***	.838						
4. Errors	.785	5.409	.998	.172*	.206**	−.009	.742					
5. Secondary use	.779	6.279	1.003	.087	.139	−.032	.454***	.649				
6. Unauthorized access	.209	6.309	.953	.105	.009	.103	.232**	−.044	.502			
7. Repatronage intentions	.872	4.262	1.245	.353***	.227*	−.355***	.070	−.086	.200	.833		
8. Store image	.941	3.866	1.526	.226**	.195*	−.367***	.141	−.013	.102	.776***	.917	
9. Intention to use medium	.919	4.318	1.386	.884***	.671***	−.496***	.134	.119	.122	.400***	.327***	.889

n = 160 and the square root of the AVEs are on the diagonal
* <.05; ** <.01; *** <.001

Table 5 Reliabilities, descriptive statistic, correlations, and AVEs (mobile scanning mobile payment)

	ICR	Mean	SD	1	2	3	4	5	6	7	8	9
1. Usefulness	.965	4.475	1.554	.933								
2. Ease of use	.808	5.410	.968	.712***	.722							
3. Collection	.895	4.633	1.401	−.309***	−.245**	.859						
4. Errors	.250	5.634	1.030	.022	.084	.186*	.542					
5. Secondary use	.897	6.325	1.042	−.073	.180*	.268***	.370***	.828				
6. Unauthorized access	.754	6.400	.951	−.025	.157	.290***	.345***	.544***	.725			
7. Repatronage intentions	.874	4.335	1.394	.256**	.245**	−.353***	−.297***	−.084	−.118	.836		
8. Store image	.957	3.872	1.688	.194*	.191*	−.429***	−.281***	−.107	−.063	.828***	.939	
9. Intention to use medium	.935	4.189	1.619	.891***	.696***	−.424***	−.045	−.080	−.002	.234***	.222***	.910

$n = 160$ and the square root of the AVEs are on the diagonal
* <.05; ** <.01; *** <.001

underlying logic that links emerging shopping technologies to the critical outcomes studied here.

First, we proposed that customers' perceptions of technology enablers (i.e., usefulness and ease of use of emerging services) would positively affect outcome evaluations. We found partial support for this proposition because there was a positive effect of technology enablers on intention to use medium. In other words, we found that customers' usefulness perceptions associated with emerging services were significant predictors of intention to use medium in all four scenarios, and that ease of use was positively associated with intention to use medium in mobile scanning scenarios.

Second, we proposed that customers' privacy concerns associated with emerging services would negatively affect shopping evaluations. We also found partial support for our second proposition because we found a negative effect for collection on outcome evaluations. In other words, we found that customers' privacy concerns about the amount of their personal information (i.e., collection) that is collected through emerging services negatively impact upon their repatronage intentions and store image in all four scenarios. We further found that collection had a negative effect on intention to use medium in mobile scanning scenarios.

Considering the fact that our sample was drawn from the target population of a general consumer pool that was developed to represent the US population, and that it matched the sampling frame of the research firm, we consider our sample to be randomly collected. This satisfies a criterion for external validity of our results because the average causal relationships observed in our sample is likely to be the same as the average causal relationship that would have been observed in other random samples drawn from the target population (Cook and Campbell 1979; Shadish et al. 2002). Therefore, our findings likely hold for other populations and generalizable in other similar contexts, such as the use of location-based services provided by mobile technologies.

6 Discussion

Motivated by existing work on service operations and an increased interest in capturing big data in retail environments, we developed a model to better understand how to leverage big data in a retail environment and employ technologically mediated POS processes as part of service operations. We initially conducted store intercept surveys to better understand customers' perceptions of emerging technologies in retail stores. Next, to further the insights gained through the in-store survey, we conducted two focus group discussions involving customers who provided us with valuable feedback regarding our shopping scenarios. The in-store survey and focus group discussions helped us to reconfirm four service scenarios that considered two technology design features (i.e., scanning and payment), each of which had two modes—fixed/mobile. These service scenarios were used in a large scale online survey involving customers ($n = 442$) who provided reactions to the emerging shopping scenarios. Our findings provide valuable insights for researchers and practitioners. First, we found that customers perceived emerging service processes to be useful in their shopping. This perception in turn had a positive impact on customers' intention to use the emerging services in their shopping trips in all four scenarios (i.e., combination of mobile/fixed scanning and mobile/fixed payment). Second, we found that mobile scanning configurations produced opposing effects on customers' intention to use the emerging services. Mobile scanning, on the one hand, was perceived favorably by customers in terms of ease of use, which in turn positively influenced their intentions to use the medium. On the other hand, the combination of

Table 6 Results of PLS analysis

Dependent variable	Independent variable	Fixed scanning fixed payment		Fixed scanning mobile payment		Mobile scanning fixed payment		Mobile scanning mobile payment	
		R^2	β	R^2	β	R^2	β	R^2	β
Repatronage intentions	Usefulness	.592	−.048	.385	.159	.222	.215	.226	.104
	Ease of use		.276		.050		−.027		.118
	Collection		−.601***		−.471***		−.284**		−.259**
	Errors		.135		−.128		.049		−.290
	Secondary use		.028		.109		−.124		.081
	Unauthorized access		−.048		−.120		.190		−.003
Store image	Usefulness	.509	.170	.251	.104	.173	.003	.253	.031
	Ease of use		−.032		−.056		.021		.073
	Collection		−.630***		−.404**		−.368***		−.393***
	Errors		.017		−.100		.151		−.263
	Secondary use		−.076		.080		−.092		.019
	Unauthorized access		.216		−.187		.100		.120
Intention to use medium	Usefulness	.896	.731***	.849	.882***	.805	.750***	.831	.766***
	Ease of use		.251		.014		.146*		.105
	Collection		.016		−.063		−.075		−.168***
	Errors		−.030		−.022		−.073		−.060
	Secondary use		−.090		.062		.067		−.020
	Unauthorized access		−.021		−.020		.069		.081

* $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$

mobile scanning and mobile payment raised customers' privacy concerns over the amounts of information (i.e., collection) that they gave to retailers, which in turn had a negative effect on customers' intentions to use the medium. Finally, we found that extensive amounts of customers' information, i.e., collection, that were being collected through the emerging service processes had negative impacts on their repatronage intentions and perceptions of store image under all four scenarios.

6.1 Implications for research

Mobile shopping services along with big data analytics can assist retailers to more effectively service customers through collecting and analyzing large volume of evidence-based data in retail environment (Wang et al. 2016). Customers' responses to such emerging services are a source of big data, that if leveraged appropriately, can lead to more successful service operations in retail stores. To the best of our knowledge, our work is among the first studies having developed a theoretically motivated model in this context. The growing literature on big data analytics has primarily focused on development of theoretical understanding on how firms can leverage big data to customize product offerings based on customers' purchase preferences (e.g., Aloysius et al. 2016; Fosso Wamba et al. 2012). We complement this literature by developing a model that elaborates on the underlying logic of customers' reactions to in-store emerging shopping technologies and links customers' perceptions of service processes to their perceptions of service providers (i.e., retailers). More specifically, we distinguished between customers' positive and negative perceptions of emerging service processes and found the linkage between such determining perceptions and customers' subsequent use intention as well as perceptions about the retail stores that have employed the emerging technologies. Future research could build on our findings and develop a greater understanding of the interrelationships between emerging service processes and critical shopping outcomes.

Second, our work extends research on opportunities and obstacles of emerging service processes in retail stores. In other words, little work on emerging services has studied factors that lead to both gains and losses of big data initiatives in retail environment. We, however, argued and found that besides the benefits of exploitation of big data through emerging services, there is at least one impediment to retailers' progress: customers' privacy concerns especially over the volume of their personally identifiable data that is captured during their shopping trips. In other words, although usefulness and ease of use of emerging services increase customers' intentions to adopt these services (especially when product scanning can be done in a mobile fashion), customers' privacy concerns over the excessive collection of their personal information discourage them to use emerging technologies and incur significant costs to retailers by negatively affecting customers' perceptions of the retail stores and their intention to return to the stores. Our framework can provide a useful basis for future work to provide more insights into the negative effects of such services by examining more nuanced components of privacy concerns, such as customers' awareness of, and control over, retailers' privacy practices (Malhotra et al. 2004).

Third, and related to the previous implication, we contextualize technology adoption (Davis and Venkatesh 2004) and privacy calculus (Dinev and Hart 2006) theories and found support for them in the context of emerging services and cutting-edge technologies. Advances in theory development highlight the importance of contextualization in theory building because context-specific theories reveal richer insights and more precise explanations (Alvesson and Kärreman 2007; Bamberger 2008; Johns 2006). As such, we found that technology enablers (i.e., usefulness and ease of use) stand significant in predicting customers' intentions to use the emerging services. Similarly, privacy calculus justification holds true in the context of emerging services. That is, we found no evidence that customers' privacy concerns over the errors that may be made in their personal information (i.e., errors), the possible misuse of their private information (i.e., secondary use), and the probable access of unauthorized entities to their information (i.e., unauthorized access) inhibit them from using the emerging services or harm other outcome evaluations. This may be owing to the fact that individuals engage in a privacy calculus (i.e., a tradeoff between costs and benefits) when deciding whether or not to use a potentially privacy invasive technology (Culnan and Armstrong 1999; Dinev and Hart 2006). As articulated by the privacy calculus argument, individuals may sacrifice their privacy to some extent to derive some benefits in return (Chellappa and Sin 2005; Culnan and Bies 2003; Dinev and Hart 2006; Laufer and Wolfe 1977).

6.2 Implications for practice

Emerging technologies and services could enable retailers to collect big data in real time and subsequently give them insights into their customer offerings (Aloysius et al. 2016). But, the fulfilment of such valuable functions is only possible if customers adopt and use these technologies in retail stores (Aloysius et al. 2016; Venkatesh et al. 2017). Given this precondition for exploitation of big data initiatives, our findings bring benefits to retail managers and practitioners for two main reasons. First, we found that customers' perceptions of usefulness of the emerging services have a positive impact on their intention to use the service irrespective of the service process characteristics (i.e., fixed/mobile scanning and fixed/mobile payment). We, however, found that perceived ease of use is associated with intention to use the service solely under mobile scanning scenarios. This could suggest that use of fixed scanning services is not sufficiently perceived to be effortless to affect customers' intentions to use them. In other words, customers prefer mobile to fixed scanning because scanning the product in a mobile fashion gives them flexibility to compare different products and make their purchase decisions while browsing the aisles in a retail store. Further, locating fixed scanning points in retail stores could be frustrating. Thus, the choice of a particular emerging service may be determined by customers' perceptions of ease of use than usefulness of these services as we found no differences among the four scenarios in terms of customers' perceived usefulness. This implies that practitioners can increase customers' intended use of emerging services by employing the mobile scanning configurations in their retail stores.

Second, we found that one component of customers' privacy concerns (i.e., collection), which closely corresponds to big data's main characteristic (i.e., volume), had a negative effect on both customers' repatronage intentions and store image regardless of the service configurations. In other words, customers' privacy concerns over the large volume of their personal data which is collected through retailers' emerging technologies and their big data initiatives inhibit them from perceiving a pleasant image of the store and returning to the store. This clearly cautions practitioners, intending to exploit customers' big data, to keep collection of customers' information in check. Although future studies are needed to shed light on the manner in which retailers can reduce their queries about the customers' information while collecting a fair amount of data from them, we draw practitioners' attention to the negative impact that collection of too much personal information can make on their outcomes.

6.3 Limitations and future research directions

We note that our work has at least two interrelated limitations. First, for practical reasons, our study has a cross-sectional rather than longitudinal design. That is, the data for both IVs and DVs are collected from the same individuals in the same measurement context at one point in time. This imposes the other limitation on our work that the observed correlations between those variables could be inflated because of the spurious variance that is attributable to the cross-sectional design (Podsakoff et al. 2003). It has been widely discussed that cross-sectional studies of the relationships between attitude and behavior are susceptible to the inflation of correlations by common method variance (Lindell and Whitney 2001). Especially, under typical empirical circumstances of testing technology adoption, there is "inherent common methods biasing because all measures are self-reported and undoubtedly tied together in the minds of the respondents" (Straub et al. 2004, p. 389). This could explain why we find high correlations (e.g., .936) between usefulness and intention to use medium, that question our discriminant validity even though we adapted previously validated scales from Froehle and Roth (2004) and Venkatesh et al. (2003). To overcome such limitations, we suggest that future studies split the data collection into two or more waves and use longitudinal designs that are generally considered to be more robust against common method bias (Lindell and Whitney 2001).

7 Conclusions

Drawing on research on emerging service processes in retail stores (Aloysius et al. 2016), we used four particular configurations of scanning and payment scenarios and studied customers' reactions to these scenarios. Investigating the effect of drivers (i.e., technology enablers) and inhibitors (i.e., privacy concerns) of emerging services on critical outcomes that give retailers competitive advantage in the era of big data, we found the missing link between customers' perceptions of emerging service processes and their perceptions of service providers (i.e., retailers). Our work is among the first few studies that sheds light into pioneering retailers' departure from the traditional sales channels to the alternative superior channels that allow retailers to exploit big data and consequently provide substantial mutual benefits to their customers and themselves.

Appendix 1: Demographics of scenario survey respondents

Demographic	Category	Percentage
Gender	Men	42.3
	Women	57.7
Age groups	Under 20	5.0
	20–29	63.1
	30–39	17.9
	40–49	8.1
	50–59	4.8
	60 or older	1.1
Annual income (in USD)	Under 10,000	12.9
	10,000–19,000	9.3
	20,000–29,000	12.9
	30,000–39,000	9.5
	40,000–49,000	10.6
	50,000–74,000	19.7
	75,000–99,000	14.0
	100,000–150,000	7.7
	Over 150,000	3.4
Job	Banking and finance	29.7
	Education	1.6
	Engineering	7.7
	Government and military	3.6
	ICT	34.6
	Insurance and real estate	13.3
	Marketing and advertising	1.4
	Retail and wholesale	2.9
	Student	1.8
	Other	3.4

n = 442

Appendix 2: Example of an emerging shopping scenario

Thank you for agreeing to participate in our Mobile Shopping study. This is what mobile shopping means. Imagine that on your visit to the store you select all the items you would like to purchase. You take your shopping cart to an employee who scans all items you put into your shopping cart. The picture below illustrates the mobile scanning process.

Once you have completed shopping, you take your shopping cart to the checkout area. The checkout area is equipped with mobile payment terminals that can access the information stored on the employee's mobile scanning device. To check out, you swipe your mobile phone over the terminal and authorize the payment on your mobile phone. The picture below illustrates the mobile payment process.

References

Aloysius, J. A., & Venkatesh, V. (2013). *Mobile point-of-sale and loss prevention: An assessment of risk*. Retail Industry Leaders Association. http://waltoncollege.uark.edu/lab/JAloysius/RILA%20Report/MobilePOSReport.pdf. Accessed 11 April 2016.

Aloysius, J. A., Hoehle, H., & Venkatesh, V. (2016). Exploiting big data for customer and retailer benefits: A study of emerging mobile checkout scenarios. *International Journal of Operations & Production Management*, *36*(4), 467–486.

Altintas, N., & Trick, M. (2014). A data mining approach to forecast behavior. *Annals of Operations Research*, *216*(1), 3–22.

Alvesson, M., & Kärreman, D. (2007). Constructing mystery: Empirical matters in theory development. *Academy of Management Review*, *32*(4), 1265–1281.

Angst, C. M., & Agarwal, R. (2009). Adoption of electronic health records in the presence of privacy concerns: The elaboration likelihood model and individual persuasion. *MIS Quarterly*, *33*(2), 339–370.

Baesens, B., Bapna, R., Marsden, J. R., Vanthienen, J., & Zhao, J. L. (2014). Transformational issues of big data and analytics in networked business. *MIS Quarterly*, *38*(2), 629–631.

Baker, J., Grewal, D., & Parasuraman, A. (1994). The influence of store environment on quality inferences and store image. *Journal of the Academy of Marketing Science*, *22*(4), 328–339.

Bamberger, P. (2008). From the editors beyond contextualization: Using context theories to narrow the micro-macro gap in management research. *Academy of Management Journal*, *51*(5), 839–846.

Blodgett, J. G., Hill, D. J., & Tax, S. S. (1997). The effects of distributive, procedural, and interactional justice on postcomplaint behavior. *Journal of Retailing*, *73*(2), 185–210.

Brown, S. A. (2008). Household technology adoption, use, and impacts: Past, present, and future. *Information Systems Frontiers*, *10*(4), 397–402.

Brown, S. A., Chervany, N. L., & Reinicke, B. (2007). What matters when introducing new information technology? *Communications of the ACM*, *50*(9), 91–96.

Brown, S. A., Massey, A. P., & Ward, K. (2016). Handle mergers and acquisitions with care: The fragile nature of the user IT-service provider relationship. *European Journal of Information Systems*, *25*(2), 170–186.

Chellappa, R. K., & Shivendu, S. (2010). Mechanism design for "free" but "no free disposal" services: The economics of personalization under privacy concerns. *Management Science*, *56*(10), 1766–1780.

Chellappa, R. K., & Sin, R. G. (2005). Personalization versus privacy: An empirical examination of the online consumer's dilemma. *Information Technology and Management*, *6*(2–3), 181–202.

Chen, W., Song, J., Shi, L., Pi, L., & Sun, P. (2013). Data mining-based dispatching system for solving the local pickup and delivery problem. *Annals of Operations Research*, *203*(1), 351–370.

Chongwatpol, J. (2015). Integration of RFID and business analytics for trade show exhibitors. *European Journal of Operational Research*, *244*(2), 662–673.

Christopher, M., & Ryals, L. J. (2014). The supply chain becomes the demand chain. *Journal of Business Logistics*, *35*(1), 29–35.

Chronopoulos, M., & Siddiqui, A. (2015). When is it better to wait for a new version? Optimal replacement of an emerging technology under uncertainty. *Annals of Operations Research*, *235*(1), 177–201.

Cook, T. D., & Campbell, D. T. (1979). *Quasi-experimentation: Design & analysis issues for field settings*. Boston, MA: Houghton Mifflin.

Culnan, M. J., & Armstrong, P. K. (1999). Information privacy concerns, procedural fairness, and impersonal trust: An empirical investigation. *Organization Science*, *10*(1), 104–115.

Culnan, M. J., & Bies, R. J. (2003). Consumer privacy: Balancing economic and justice considerations. *Journal of Social Issues*, *59*(2), 323–342.

Davis, F. D., & Venkatesh, V. (2004). Toward preprototype user acceptance testing of new information systems: Implications for software project management. *IEEE Transactions on Engineering Management*, *51*(1), 31–46.

Day, G. S., Schoemaker, P. J. H., & Gunther, R. E. (2004). *Wharton on managing emerging technologies*. New York: Wiley.

Dinev, T., & Hart, P. (2006). An extended privacy calculus model for e-commerce transactions. *Information Systems Research*, *17*(1), 61–80.

Dinev, T., McConnell, A. R., & Smith, H. J. (2015). Research commentary–Informing privacy research through information systems, psychology, and behavioral economics: Thinking outside the "APCO" box. *Information Systems Research*, *26*(4), 639–655.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50.

Fosso Wamba, S., Edwards, A., & Sharma, R. (2012). *Big data as a strategic enabler of superior emergency service management: Lessons from the New South Wales State Emergency Service*. Society for Information Management and MIS Quarterly Executive Pre-ICIS 2012 SIM Academic Workshop, 1-3.

Fosso Wamba, S., Akter, S., Coltman, T., & Ngai, E. W. T. (2015a). Guest editorial: Information technology-enabled supply chain management. *Production Planning & Control*, *26*(12), 933–944.

Fosso Wamba, S., Akter, S., Edwards, A., Chopin, G., & Gnanzou, D. (2015b). How 'big data' can make big impact: Findings from a systematic review and a longitudinal case study. *International Journal of Production Economics*, *165*, 234–246.

Froehle, C. M., & Roth, A. V. (2004). New measurement scales for evaluating perceptions of the technology-mediated customer service experience. *Journal of Operations Management*, *22*(1), 1–21.

Goller, B., & Hoffmann, S. (2013). Leveraging big data for precision in-store marketing: Turning real-time data into big-time insights. *Retail Property Insights*, *20*(1), 30–36.

Grace, D., & O'Cass, A. (2005). An examination of the antecedents of repatronage intentions across different retail store formats. *Journal of Retailing and Consumer Services*, *12*(4), 227–243.

Guan, J. C., Yam, R. C., Mok, C. K., & Ma, N. (2006). A study of the relationship between competitiveness and technological innovation capability based on DEA models. *European Journal of Operational Research*, *170*(3), 971–986.

Günther, O., & Spiekermann, S. (2005). RFID and the perception of control: The consumer's view. *Communications of the ACM*, *48*(9), 73–76.

Hair, J. F., Anderson, R. E., Tatham, R. L., & Black, W. C. (1998). *Multivariate data analysis* (5th ed.). Englewood Cliffs, NJ: Prentice-Hall.

Hong, W., & Thong, J. Y. L. (2013). Internet privacy concerns: An integrated conceptualization and four empirical studies. *MIS Quarterly*, *37*(1), 275–298.

Houston Chronicle (2016). http://smallbusiness.chron.com/push-vs-pull-supply-chain-strategy-77452.html. Accessed 11 April 2016.

Hui, K. L., Teo, H. H., & Lee, S. Y. T. (2007). The value of privacy assurance: An exploratory field experiment. *MIS Quarterly*, *33*(1), 19–33.

Johns, G. (2006). The essential impact of context on organizational behavior. *Academy of Management Review*, *31*(2), 386–408.

Kou, G., & Lou, C. (2012). Multiple factor hierarchical clustering algorithm for large scale web page and search engine clickstream data. *Annals of Operations Research*, *197*(1), 123–134.

Laufer, R. S., & Wolfe, M. (1977). Privacy as a concept and a social issue: A multidimensional developmental theory. *Journal of Social Issues*, *33*(3), 22–42.

Laufer, R. S., Proshansky, H. M., & Wolfe, M. (1974). Some analytic dimensions of privacy. In R. Kuller (Ed.), *Architectural psychology: Proceedings of the lund conference* (pp. 353–372). Stroudsburg, PA: Dowden, Hutchinson, and Ross.

Lindell, M. K., & Whitney, D. J. (2001). Accounting for common method variance in cross-sectional research designs. *Journal of Applied Psychology*, *86*(1), 114–121.

Malhotra, N. K., Kim, S. S., & Agarwal, J. (2004). Internet users' information privacy concerns (IUIPC): The construct, the scale, and a causal model. *Information Systems Research*, *15*(4), 336–355.

Maull, R., Geraldi, J., & Johnston, R. (2012). Service supply chains: A customer perspective. *Journal of Supply Chain Management*, *48*(4), 72–86.

Nunnally, J. C. (1978). *Psychometric theory*. New York, NY: McGraw-Hill.

Ohkubo, M., Suzuki, K., & Kinoshita, S. (2005). RFID privacy issues and technical challenges. *Communication of the ACM*, *48*(9), 66–71.

Pavlou, P. A. (2011). State of the information privacy literature: Where are we now and where should we go. *MIS Quarterly*, *35*(4), 977–988.

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879–903.

Rai, A., & Bajwa, D. S. (1997). An empirical investigation into factors relating to the adoption of executive information systems: An analysis of EIS for collaboration and decision support. *Decision Sciences*, *28*(4), 939–974.

Rai, A., & Patnayakuni, R. (1996). A structural equation model for CASE adoption behaviour. *Journal of Management Information Systems*, *13*(2), 205–234.

Ringle, C. M., Wende, S., & Becker, J. M. (2005). *Smart PLS 2.0*. http://www.smartpls.de. Accessed 13 Dec 2015.

RIS Research. (2015). *Store systems study: Making stores matter*. http://risnews.edgl.com/retail-research/2015-RIS/IHL-Store-Systems-Study--Making-Stores-Matter97362. Accessed 11 April 2016.

Sampson, S. E., & Spring, M. (2012). Customer roles in service supply chains and opportunities for innovation. *Journal of Supply Chain Management*, *48*(4), 30–50.

Schoenherr, T., & Speier-Pero, C. (2015). Data science, predictive analytics, and big data in supply chain management: Current state and future potential. *Journal of Business Logistics*, *36*(1), 120–132.

Shadish, W. R., Cook, T. D., & Campbell, D. T. (2002). *Experimental and quasi-experimental designs for generalized causal inference*. Belmont, CA: Wadsworth Cengage learning.

Simmons, D. D. (1965). Invasion of privacy and judged benefit of personality-test inquiry. *Journal of General Psychology*, *79*, 77–81.

Singh, J. (1988). Consumer complaint intentions and behavior: Definitional and taxonomical issues. *The Journal of Marketing*, *52*(1), 93–107.

Smith, H. J., Dinev, T., & Xu, H. (2011). Information privacy research: An interdisciplinary review. *MIS Quarterly*, *35*(4), 989–1016.

Smith, H. J., Milberg, S. J., & Burke, S. J. (1996). Information privacy: Measuring individuals' concerns about organizational practices. *MIS Quarterly*, *20*(2), 167–196.

Straub, D., Boudreau, M. C., & Gefen, D. (2004). Validation guidelines for IS positivist research. *The Communications of the Association for Information Systems*, *13*(1), 380–427.

Thong, J. Y. L., Hong, W., & Tam, K. Y. (2002). Understanding user acceptance of digital libraries: What are the roles of interface characteristics, organizational context, and individual differences? *International Journal of Human–Computer Studies*, *57*(3), 215–242.

Thong, J. Y. L., Hong, S. J., & Tam, K. Y. (2006). The effects of post-adoption beliefs on the expectation-confirmation model for information technology continuance. *International Journal of Human–Computer Studies*, *64*(9), 799–810.

Venkatesh, V., Hoehle, H., Aloysius, J. A., & Burton, S. (2017). Leveraging customers' mobile devices and auto-ID technologies in an in-store design and evaluation of auto-ID enabled shopping assistance artifacts: Two retail store laboratory experiments. *MIS Quarterly*.

Venkatesh, V., & Agarwal, R. (2006). Turning visitors into customers: A usability-centric perspective on purchase behavior in electronic channels. *Management Science*, *52*(3), 367–382.

Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences*, *39*(2), 273–315.

Venkatesh, V., Brown, S. A., Maruping, L. M., & Bala, H. (2008). Predicting different conceptualizations of system use: The competing roles of behavioral intention, facilitating conditions, and behavioral expectation. *MIS Quarterly*, *32*(3), 483–502.

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, *46*(2), 186–204.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425–478.

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, *36*(1), 157–178.

Wang, G., Gunasekaran, A., Ngai, E. W. T., & Papadopoulos, T. (2016). Big data analytics in logistics and supply chain management: Certain investigations for research and applications. *International Journal of Production Economics*, *176*, 98–110.

Wirthman, L. (2013). *Forbes*. http://www.forbes.com/sites/emc/2013/12/16/what-your-cellphone-is-telling-retailers-about-you/#7196cb71df22. Accessed 11 April 2016.

Wixom, B. H., & Todd, P. A. (2005). A theoretical integration of user satisfaction and technology acceptance. *Information Systems Research*, *16*(1), 85–102.

Zhong, R. Y., Huang, G. Q., Lan, S., Dai, Q. Y., Chen, X., & Zhang, T. (2015). A big data approach for logistics trajectory discovery from RFID-enabled production data. *International Journal of Production Economics*, *165*, 260–272.