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Technology sourcing for website personalization and social media marketing: A study of e-retailing industry☆

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ABSTRACT

Extant streams of literature on technology sourcing, website personalization and social media marketing are distinct from one another and hence are unable to explain the impact of technology sourcing for website personalization and social media marketing on sales. To address this gap, we use various concepts such as efficiency, adaptability, risks of dependency, lack of quality control, asset-specificity and tacit knowledge to hypothesize the direct effect of technology sourcing on sales as well as the indirect effect through social media performance. Using survey data from 105 U.S. e-retailers, we show that e-retailers using mixed technology sourcing for website personalization have greater sales than e-retailers that use either internally or externally developed technology. On the contrary, e-retailers selecting externally developed technology for social media marketing have greater sales than e-retailers that offer social media marketing that uses either internally developed technology or mixed technology sourcing.

1. Introduction

The Web has made one-to-one marketing eminently possible by allowing e-retailers to implement website personalization (WP) and social media marketing (SMM) (Ho, 2006; Kaptein & Parvinen, 2015). The digital nature of the Web has created opportunities for e-retailers to quickly collect and analyze customer data at a low cost and provide unique content of direct relevance to each customer (Ho & Bodoff, 2014). However, e-retailers are using different technology sources for implementing WP and SMM; and are experiencing substantial heterogeneity in market performance. Let's consider the following examples. In 2012, Wal-Mart started 'Pangaea', a process to develop its e-retailing website from scratch. It meant changing the underlying transaction software, database servers, creating its own search engine, and the backend data center tools to manage it all. Wal-Mart opted for in-house technology sourcing for WP and SMM; but despite these efforts at creating in-house expertise, its sales have not improved until today.[1] In contrast to Wal-Mart, BestBuy.com uses external technology vendors for WP and SMM. The revenue of BestBuy.com continues to grow every year.[2] As these examples indicate, there is heterogeneity in the technology sourcing decisions for WP and SMM, across e-retailers.

The existing literature on technology sourcing across marketing strategy and information systems research fails to explain whether the effect on sales performance is likely to be higher for e-retailers that develop the technology for WP and SMM in-house or those that outsource these technologies. This is surprising given the vast number of papers on these topics. The most plausible explanation for this important gap in existing literature is that there are distinct and separate literature streams on technology sourcing, WP and SMM. The literature on technology sourcing can be divided into three main streams. The first stream of literature provides alternative explanations from social, economic, and political points of view for outsourcing decisions (Han & Mithas, 2013). The second stream focuses on the client–supplier relationship, analyzing its characteristics, its partnership quality, and the impact of these on outsourcing success (Fitoussi & Gurbaxani, 2012; Goo, Kishore, Rao, & Nam, 2009). The third stream studies the advantages and disadvantages of in-house technology development versus outsourcing, and the impact of technology sourcing decision on outcome (Nam, Rajagopalan, Rao, & Chaudhury, 1996) but does not address the context of technology sourcing for WP or SMM.

Further, there are three existing streams of literature on WP. The first stream of literature discusses the effects of personalization on customer privacy (Piotrowicz & Cuthbertson, 2014; Zhao, Lu, & Gupta, 2012). The second stream focuses on the impact of WP on various

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[1] http://fortune.com/2015/10/14/walmart-weak-sales/; accessed on 04/03/2016
[2] https://www.internetretailer.com/2015/11/19/web-sales-drive-all-growth-best-buy; accessed on 04/03/2016

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performance metrics (Choi, Lee, & Kim, 2011). WP improves customer experience (Li & Unger, 2012); increases satisfaction (Komiak & Benbasat, 2006); trust, loyalty and switching cost (Choeh & Lee, 2008); increases customer's confidence in their choice (Cai & Xu, 2011); and impacts customer's decision-making process (Komiak & Benbasat, 2006). The third stream studies the effect of customer-level variables like content relevance, self-reference, and customer's need for cognition on the performance of WP (Tam & Ho, 2006).

Finally, the literature on social media is recent and empirical research is limited. The three main streams of literature on SMM are as follows. The first stream of literature focuses on how and why companies are adopting social media for marketing (Du & Jiang, 2014). Culnan, McHugh, and Zubillaga (2010) noted the use of social media in marketing and the Fortune 500 companies' use of four of the most popular social media platforms-Twitter, Facebook, blogs, and client-hosted forums-to interact with customers. Miranda, Kim, and Summers (2015) identified the use of social media for brand promotion as one of four major ways in which Fortune companies used social media between 2006 and 2012. The second stream, though scant, relates SMM to firm performance. Rishika, Kumar, Janakiraman, and Bezawada (2013) show the positive impact of customers' social media participation on firm profitability. Luo, Zhang, and Duan (2013) suggest that social media-based metrics (Web blogs and consumer ratings) are significant indicators of firm equity value. The third stream questions how little is known about the different resources and capabilities that organizations deploy internally to support SMM initiatives (Alfaro & Watson-Manheim, 2015; Felix, Rauschnabel, & Hinsch, 2016).

In this paper, we contribute to all three literature streams by synthesizing them and studying *the effect of technology sourcing choices for website personalization and social media marketing on e-retailer's sales performance*. This is an important and crucial knowledge gap because the delivery of automated processes, like WP and SMM, depends upon the implementation of the relevant technology.

We test our arguments using data from the U.S. e-retailing industry. We have a representative sample of 105 e-retailers from the Internet Retailer (Editions 2014, 2015 and 2016). Our results show that e-retailers opting for mixed technology sourcing for WP have the highest sales performance, whereas e-retailers selecting external sourcing for SMM have the highest social media and sales performance. In the next sections, we define our key variables and develop our framework. We then describe our research context and method. The concluding sections present our results and implications.

2. Theory and hypotheses

2.1. Definitions

Technology sourcing is the extent to which a firm relies on a third party's expertise versus efforts of its own staff to develop the core components of a technology for further use (Henderson & Clark, 1990; Weigelt, 2009). If a firm depends on its own staff, invests financial and managerial resources, and does in-house R & D in order to develop the core technological components then it is using *internally developed technology* (Veugelers, 1997; Weigelt, 2009). Whereas, if a firm depends on a third party vendor, to whom it subcontracted to provide the core technological components, then it is using *externally developed technology* (Klepper, 1995; Weigelt, 2009). Further, if a firm invests in equipment, staff coordination and R & D for some core technological components, while also engaging in selecting, negotiating with, and maintaining external technology suppliers for other core technological components, then they are involved in *mixed technology sourcing* (Krzeminska, Hoetker, & Mellewigt, 2013). *Website personalization* is a process for creating individualized web content that includes, but is not limited to, content concerning the product, promotional communication, and pricing. WP is firm-initiated and firm-driven and does not require the user's explicit input or control to generate individualized content (Bodoff & Ho, 2015). It is an automated technological process that identifies a web user, collects navigation patterns of the user, analyzes known preferences of similar users, and estimates his or her specific preferences to tailor web content for each user (Lavie, Sela, Oppenheim, Inbar, & Meyer, 2010). Depending on the type of web content that is tailored, there are numerous specialized WP applications (Kaptein & Parvinen, 2015). For example, recommender systems tailor a user's home page by recommending a specific set of products that match the user's preferences (Choi et al., 2011). Other WP applications focus on offering individualized price quotes, individualized search results, individualized advertisements or promotions based on the user's browsing history (Hauser, Urban, Liberali, & Braun, 2009; McFarland, Challagalla, & Shervani, 2006). The goal of providing individualized web content relevant to each user's needs is to influence the user's decision-making process (Zanker, Ricci, Jannach, & Terveen, 2010).[3] *Social media marketing* is a form of Internet marketing that utilizes media platforms as a marketing tool. The goal of SMM is to produce tailored content that users will share with their social network to help a company increase brand exposure and broaden customer reach (Kaplan & Haenlein, 2010). *Social media success* is defined as positive conversations about a firm and its products on social media platforms (Vries, Gensler, & Leeflang, 2012). The number of 'likes' on a particular post and the number of 'followers' a company has on various social media platforms shows its success on social media. *Sales performance* is the monetary value of goods sold by an e-retailer.

2.2. Theoretical framework

In our theoretical framework we use the concepts of efficiency, adaptability (Weigelt & Sarkar, 2012), tacit knowledge (Nonaka & Takeuchi, 1995), asset-specificity (Williamson, 1985), risks of dependency and lack of quality control (Ye, Zhu, & Mukhopadhyay, 2014) to develop our hypotheses and model (see Fig. 1).

2.2.1. Technology sourcing for website personalization and sales performance

There is considerable heterogeneity in sales performance across firms that make different technology sourcing choices for WP. Firms have the choice to obtain technology for implementing WP that are either externally developed or internally developed or have mixed technology sourcing. For ease of exposition, we organize our subsequent arguments according to the different technology sourcing choices.

First, recent empirical research by Weigelt and Sarkar (2012) has shown that externally developed technology increases efficiency[4] but reduces adaptability[5] resulting in a trade-off situation. The firm routines underlying use of technology from external sources are formal, standardized and replicable. Such routines support efficiency because they allow for disciplined problem solving and use existing resources and competencies. But these routines do not support adaptability since they do not allow for experimentation, novel approaches and search for new alternatives. Thus, externally developed technology increases efficiency in terms of cost and speed of transactions, but it reduces the firm's adaptability to customer's changing needs (Weigelt & Sarkar, 2012). Applying Weigelt and Sarkar's (2012) findings to the context of

[3] Another way to individualize web content is through *Customization*. Customization is a user-initiated and user-driven process (Bodoff & Ho, 2015). Users tailor the website content to their specific needs. In order to individualize, both customization and personalization require detailed information about the user, however, the difference lies in the control of the adaptation process.

[4] Efficiency refers to a firm's efforts to lower process costs and execute these processes faster (Rivkin & Siggelkow, 2003; Smith & Tushman, 2005; Tjader, Shang, Duh, & Chow, 2004; Weigelt & Sarkar, 2012).

[5] Adaptability refers to a firm's responsiveness in adjusting and altering its processes to customers' changing needs (Tjader et al., 2004; Weigelt & Sarkar, 2012).

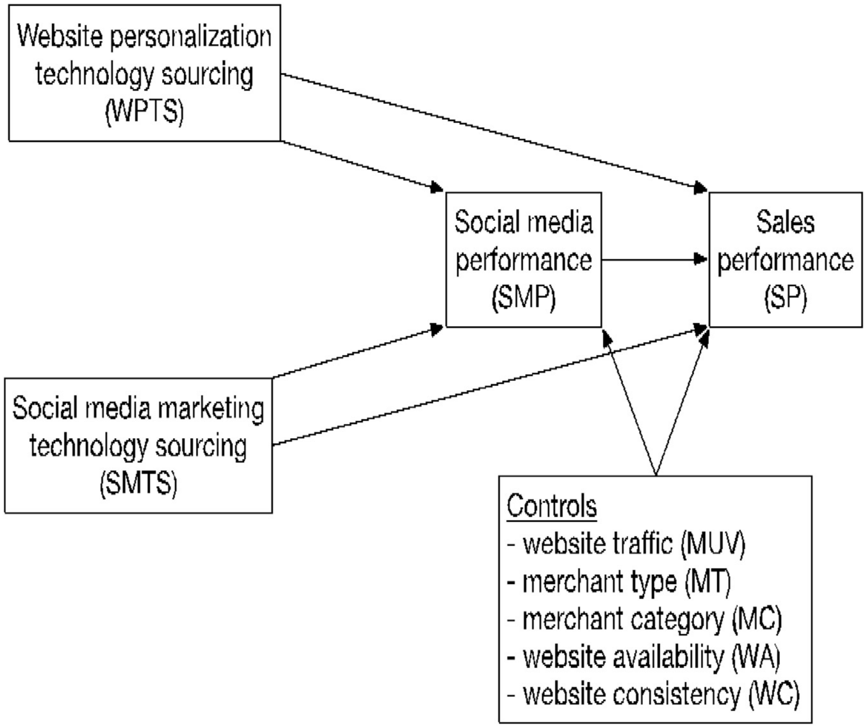

Fig. 1. Model.

WP, it follows that firms using externally developed web personalization technologies are likely to be less responsive to each individual customer's changing web personalization needs or to the heterogeneous needs of individual customers across the customer base. This lack of responsiveness causes dissatisfaction among customers (Eshagi, Roy, & Ganguli, 2008; Ye et al., 2014). Also, suppliers of technology are likely to develop a technology platform that they can offer to multiple clients as a standardized, off-the-shelf package. By developing standardized packages that have lower asset specificity as compared to customized solutions, suppliers are able to reduce probability of opportunistic behavior by the client firm (Williamson, 1985). Such packages are technology platforms that follow a standardized process to collect, analyze and use customer data and should be avoided for two reasons. First, firms using such packages lack control over the quality of their processes (Ye et al., 2014). Second, such web personalization packages do not allow differentiation between competing firms who might also apply them. Note that use of standardized packages should only be avoided when they involve processes that are crucial and can result in a competitive advantage.[6] Moreover, using only external vendors to develop WP technology can create dependency of the e-retailer on the technology vendor resulting in risks of opportunistic behavior by the vendor (Huang, Miranda, & Lee, 2004). Such risks occur because of externalization of control over critical organizational activity like WP (Ngwenyama & Bryson, 1999) along with asymmetric relationship between the e-retailer and the technology vendor (Huang et al., 2004).

Second, internally developed technology reduces efficiency but increases adaptability of the firm (Weigelt & Sarkar, 2012). Internal processes involve experimentation and search for novel approaches that increase variance and support adaptability to changing environments (Smith & Tushman, 2005). Firms also have the opportunity to develop more differentiated personalization services than those offered by standardized off-the-shelf web personalization packages (Patel, 2014) and improve their strategic competence (Lee, Miranda, & Kim, 2004). By developing technology internally firms convert specialized knowledge to habituated action (Kogut & Zander, 1996). This reduces dependence on external vendors for critical organizational resources and competencies (Pfeffer & Salancik, 1978). Further, firms that internally develop technology for WP are better able to integrate this technology with firm databases (Patel, 2014). This integration activity is crucial but specific to each e-retailer and cannot be redeployed for use of another e-retailer. The asset specificity of integrating WP technology is then high, making it more desirable for e-retailers to develop and integrate the technology internally (Williamson, 1985). But, overreliance on internally developed knowledge can result in the setting in of core rigidities (Allen, 1986; Leonard-Barton, 1992), which in turn could decrease the innovativeness and superiority of web personalization services (Dutta & Roy, 2004). Thus, firms that use internally developed web personalization technology are likely to be able to respond to the heterogeneous customer needs at a point in time or over time, although with low innovativeness and reduced efficiency.

Third, the reduced innovativeness and efficiency of firms that use internally developed technology can be countered by simultaneous external sourcing of some of the components of WP technology. The use of external vendors can serve as a source of external knowledge that keeps the firm abreast of new technical developments (Grant, 1996). Thus, the use of mixed technology sourcing allows firms to balance different activities in a trade-off situation (Rothaermel & Alexandre, 2009). We propose that ambidexterity benefits arise by balancing internally and externally developed technology resulting in greater firm performance. Ambidexterity in technology sourcing is crucial for sales performance of e-retailers for three reasons. First, efficiency ensures less effort, and greater speed of transaction between e-retailer and customer, which is necessary to satisfy and retain demanding customers (Ho, 2006). Also, empirical research has shown that the use of external technology sourcing leads to cost efficiency outcomes for e-retailers because of competitive pricing provided by vendors (see Lee et al., 2004). Second, adaptability increases firm's responsiveness in adjusting and altering systems successive to individual customer's changing web personalization needs (Eshagi et al., 2008; Ye et al., 2014). Third, the firm's absorptive capacity resulting from investments in internal technology development (Cohen & Levinthal, 1990) is likely to help the firm

[6] For example, word processing packages do not involve processes that could be a source of competitive advantage. So, in this case, use of standardized packages like Microsoft Word does not need to be avoided.

to choose an external vendor with the complementary knowledge, absorb the knowledge, transfer and exploit it to create innovative WP technology with superior features (Prabhu, Chandy, & Ellis, 2005; Todorova & Durisin, 2007). For example, in the case of data mining, continuous innovations in statistical software have expanded breadth of knowledge about data analysis techniques to artificial neural networks, genetic algorithms, decision trees, nearest neighbor method, rule induction and data visualization. E-retailers can use external vendors specialized in any one of these techniques so as to complement their current internal knowledge.

It follows from the above discussion that mixed technology sourcing allows e-retailers to (1) increase frequency and density of interactions with technology vendors so as to increase generation, utilization and distribution of knowledge (Caloghirou, Kastelli, & Tsakanikas, 2004; Nonaka & Takeuchi, 1995); (2) increase cognition of complementary knowledge (Chatterjee, 2002); (3) better leverage internal R & D activities (Allen, 1986); (4) improve the quality, and speed of new WP technology (Flanagan, 1993); and (5) reduce the asymmetry by increasing trust in their relationship with their technology vendors (Tjader et al., 2004). This implies that firms that use mixed technology sourcing for WP are likely to have higher sales. On the basis of these arguments, we hypothesize:

H1a. Firms that use mixed technology sourcing for website personalization are likely to have greater sales performance than firms that offer website personalization that has been either internally or externally developed.

2.2.2. Technology sourcing for website personalization and social media performance

Social media is an excellent medium for providing customers with personalized communication. E-retailers can create pages on social media platforms and can place posts (containing videos, messages, quizzes, information, and other material) on these platforms. Customers can become fans of these e-retailers on social media platforms, and subsequently indicate that they like e-retailers' post or comment on it. This liking and commenting on a company's posts reflects the company's popularity or success on social media (Vries et al., 2012). Some of the determinants of a company's success on social media are vividness of the posts (i.e. inclusion of dynamic animations, colors, or pictures), interactivity (i.e. two-way communication between companies and customers, as well as between customers themselves), informational and entertainment content, position of the post on the webpage, and valence of comments i.e. positive or negative comments (Vries et al., 2012). We argue that positive or negative experience on an e-retailer's website can also influence social media success. According to our arguments presented above mixed technology sourcing for WP is expected to be superior to both internally and externally developed technology in many respects, especially in satisfying customers. In particular, providing visiting customers with a better customized content (through the use of mixed technology sourcing) will encourage them to promote e-retailers on social media, by 'liking' or 'following' them. On the basis of these arguments, we hypothesize:

H1b. Firms that use mixed technology sourcing for website personalization are likely to have greater social media performance than firms that offer website personalization that has been either internally or externally developed.

2.2.3. Technology sourcing for social media marketing and social media performance

Social media pages of all e-retailers are developed and hosted on external social media platforms. The technology underlying the social media platform is exclusively developed and controlled by the social media company. This implies that the support and maintenance of social media platforms is not a responsibility of the e-retailer's IT department (Alfaro & Watson-Manheim, 2015).

Marketing campaigns on social media pages of e-retailers are exclusively developed and controlled by the e-retailer. These marketing campaigns can be tailored so as to increase attention of users, sharing of e-retailer's posts, and the popularity of the e-retailer on the social media page (Vries et al., 2012). Two-way personalized communication with individual users on social media pages is also managed by the e-retailer. E-retailers have the choice to implement these SMM activities by either using internally or externally developed technology or using mixed technology sourcing. There is considerable heterogeneity in social media performance across firms that make different technology sourcing choices for SMM. For ease of exposition, we organize our subsequent arguments according to the different technology sourcing choices for SMM.

We link externally developed technology for SMM to e-retailer performance using the concepts of efficiency and tacit knowledge. First, the use of externally developed technology increases efficiency by lowering firm expenditure in implementing automation of tailored marketing campaigns on social media (Aichner & Jacob, 2015). When this automated tailoring technology is developed in-house, organizational commitment to this technology increases and may constrain flexibility in the long term (Harrigan, 1985). Moreover, there are challenges to doing SMM internally. Felix et al. (2016) elaborate various challenges that firms doing SMM face internally with regards to: (1) decisions on scope of communication, (2) the organization and departmentalization of the SMM assignment, (3) how the company establishes rules and guidelines for SMM, and (4) how SMM responsibilities are controlled within the company. However, firms using external vendors can switch suppliers as new and more cost-effective technologies become available (Aichner & Jacob, 2015). Also, the cost of developing creative content for a SMM campaign with an agency would be between $15,000 and $18,000 per year, whereas the annual salary of a social media manager would be around $50,000. This difference is even greater if one considers that, generally, in-house employees who are given the task of SMM also have other marketing responsibilities and they tend to de-prioritize social media due to work pressure, whereas external agencies for SMM are likely to be more result-focused.[7] These external agencies will not allow for any inconsistencies in the social media activities of their client firms as their success depends on their ability to provide results to their clients.

Second, external vendors provide critical expertise that many companies lack, such as creative services, customer database management and network analysis (Alfaro & Watson-Manheim, 2015; Groza, Peterson, Sullivan, & Krishnan, 2012). Such expertise is required to provide superior tailored marketing campaigns. There is considerable heterogeneity among social media platforms in terms of their content and type of networks (Aichner & Jacob, 2015; Cho & LoCascio, 2013). External technology vendors have the tacit knowledge required to communicate effectively with diverse users across heterogeneous social media platforms through a tailored creative effort and have a sense of alignment between business model of social media platform and the e-retailer's business model. Moreover, the low asset specificity of SMM makes it easy for external vendors to transfer knowledge across clients without sacrifice of productive value (Williamson, 1985). This knowledge is crucial for success of e-retailers on different social media platforms as well as their sales performance on their e-commerce site.

Further, we link the use of internally developed technology for SMM to e-retailer performance. First, the use of internally developed technology for SMM decreases efficiency but increases adaptability of the e-retailer if individual-level data of users is available (Weigelt & Sarkar, 2012). But in the context of SMM, the raw data on users is protected by law and is available only to the social media platform. E-retailers have access to aggregated data that can be used at best to develop tailored

[7] See https://www.lyfemarketing.com/employee-or-agency-to-manage-social-media/; accessed on 23/02/2016

marketing campaigns that target groups of users. In other words, the lack of availability of individual-level data constrains adaptability of the e-retailer even when they use internally developed technology for SMM and does not allow development of unique marketing campaigns for each user. So, the use of internally developed technology for SMM does not provide any special benefits to users of e-retailers. Moreover, e-retailer expenditure in implementing SMM through the use of internally developed technology is relatively higher to the cost of using external vendors. For instance, other than the cost of research and development (Alfaro & Watson-Manheim, 2015), e-retailers that use internally developed technology also need to buy aggregated data from social media platforms. For e-retailers who use externally developed technology, this cost is considerably reduced since the external vendor buys aggregated data from the social media platform and uses this data for multiple clients.

Second, the internal creation of specialized and tacit knowledge—such as creative skills and database management—for tailored marketing campaigns will require substantial time, effort and learning by doing. By using external vendors, e-retailers can obtain quick access to this critical expertise. In addition, external vendors have developed this specialized knowledge by working with multiple clients. This allows them to aggregate diverse knowledge, which makes them more efficient than e-retailers that use internal sourcing for SMM.[8] Further, e-retailers do not have the tacit knowledge required to select relevant social media platforms that match their business model (LaDuque, 2010). This implies that e-retailers who use externally developed technology are likely to have a competitive advantage over those who choose to develop this tacit knowledge internally.

Finally, the use of mixed technology sourcing is unlikely to resolve efficiency and tacit knowledge issues resulting from use of internally developed technology for SMM. Thus, the use of externally developed technology is likely to have a better outcome in-terms of efficiency, use of relevant tacit knowledge and hence, lead to superior SMM performance. On the basis of these arguments, we hypothesize:

H2a. Firms that use externally developed technology for social media marketing are likely to have greater social media performance than firms that use internally developed technology or mixed technology sourcing for social media marketing.

2.2.4. Technology sourcing for social media marketing and sales performance

We link external sourcing for SMM to e-retailer's sales performance using the concepts of rate of clicks and user experience. First, external vendors for SMM provide highly tailored marketing campaigns. Tailored marketing campaigns increase rate of clicks for each advertisement (Robinson, Wysocka, & Hand, 2007) on social media platforms. Clicking on an advertisement on a social media platform will direct the user towards e-retailer's website, which means that an increase in the rate of clicks will increase web traffic on e-retailer's website. This has a strong impact on the sales performance of the e-retailer (Richardson, Dominowska, & Ragno, 2007).

Second, highly tailored marketing campaigns also improve user experience (Lee & Lin, 2005). Improved user experience on social media affects positively the perception of the value of a product (Bickart & Schindler, 2001), the likelihood to recommend the product (Gruen, Osmonbekov, & Czaplewski, 2006), and sales (e.g., Chintagunta, Gopinath, & Venkataraman, 2010). Hence, we hypothesize:

H2b. Firms that use externally developed technology for social media marketing are likely to have greater sales performance than firms that use internally developed technology or mixed technology sourcing for social media marketing.

[8] See https://www.lyfemarketing.com/employee-or-agency-to-manage-social-media/; accessed on 23/02/2016

2.2.5. Social media performance and sales performance

Previous studies explored the impact of social media on selling environment in general (Rodriguez, Peterson, & Krishnan, 2012) and studied the relationship between firm presence on social media and its impact on sales performance (Du & Jiang, 2014). We link e-retailer's performance on social media to its sales performance. First, greater social media performance suggests greater customer relationship management. This is because firms have managed to design communications on their products and processes on social media "to engage the customer in a collaborative conversation in order to provide mutually beneficial value in a trusted and transparent business environment" (Myron, 2010, p. 28). Greater customer relationship management leads to greater loyalty and hence greater sales performance (Reinartz, Krafft, & Hoyer, 2004).

Second, greater social media performance creates a number of opportunities for an e-retailer, in terms of marketing research and capturing new customers. Good social media performance indicates that the current customers are satisfied with a firm, are loyal to the firm and will be more open to learning about new or add-on products (Rapp, Beitelspacher, Grewal, & Hughes, 2013). Moreover, loyal customers tend to recommend the firm to others (Rapp et al., 2013), which makes attracting new customers easier. The feature of having a network of friends on different social media platforms (Kietzmann, Hermkens, McCarthy, & Silvestre, 2011) aids in capturing new customers. Capturing new customers impacts sales performance positively. Greater social media performance also provides firms a chance to conduct effective marketing research. Greater social media performance provides a firm with loyal customers who will be more likely to interact constructively with the firm and provide valuable information. This enables a firm to spot emerging market trends to get a head start in market development, rather than merely responding to feedback (Warfield, 2009). This will also impact a firm's sales performance positively. On the basis of these arguments, we hypothesize:

H3. Firms with greater social media performance are likely to have greater sales performance.

3. Methodology

3.1. Empirical context and sample

The need to study WP and SMM constrains the choice of industry for our empirical setting to one of the Internet channels. Among various Internet channels ranging from e-commerce, mobile commerce, and mobile applications to social networking sites, e-commerce is the largest and most developed Internet channel. So, we used data pertaining to the U.S. Internet retailing industry to test our hypotheses from the Internet Retailer Top 500 Guide (Editions 2014, 2015 and 2016). This guide is published every year by Vertical Web Media and provides information on the 500 largest (in terms of sales) US e-retailers. Data from this guide has been used previously in academic research by Ayanso and Yoogalingam (2009) to profile website functionalities and conversion rates; and by Haon and Patel (2011) to study the impact on performance of website functionalities used by e-retailers.

To create our dataset, we aggregated data from the 2014, 2015, and 2016 editions of the Internet Retailer Top 500 Guide. These editions contain data for the years 2013, 2014, and 2015, respectively. As shown in Fig. 2, we use data such that independent variables were always measured the year before the dependent variable. The resulting dataset has temporally separated data on technology sourcing decisions and firm performance that allows us to test our hypotheses without the possibility of backward causality. Since, backward causality is one of the important sources of endogeneity, the temporal structure of our dataset reduces the risk of correlation between our independent variables and error terms during estimation of the model presented in Fig. 1.

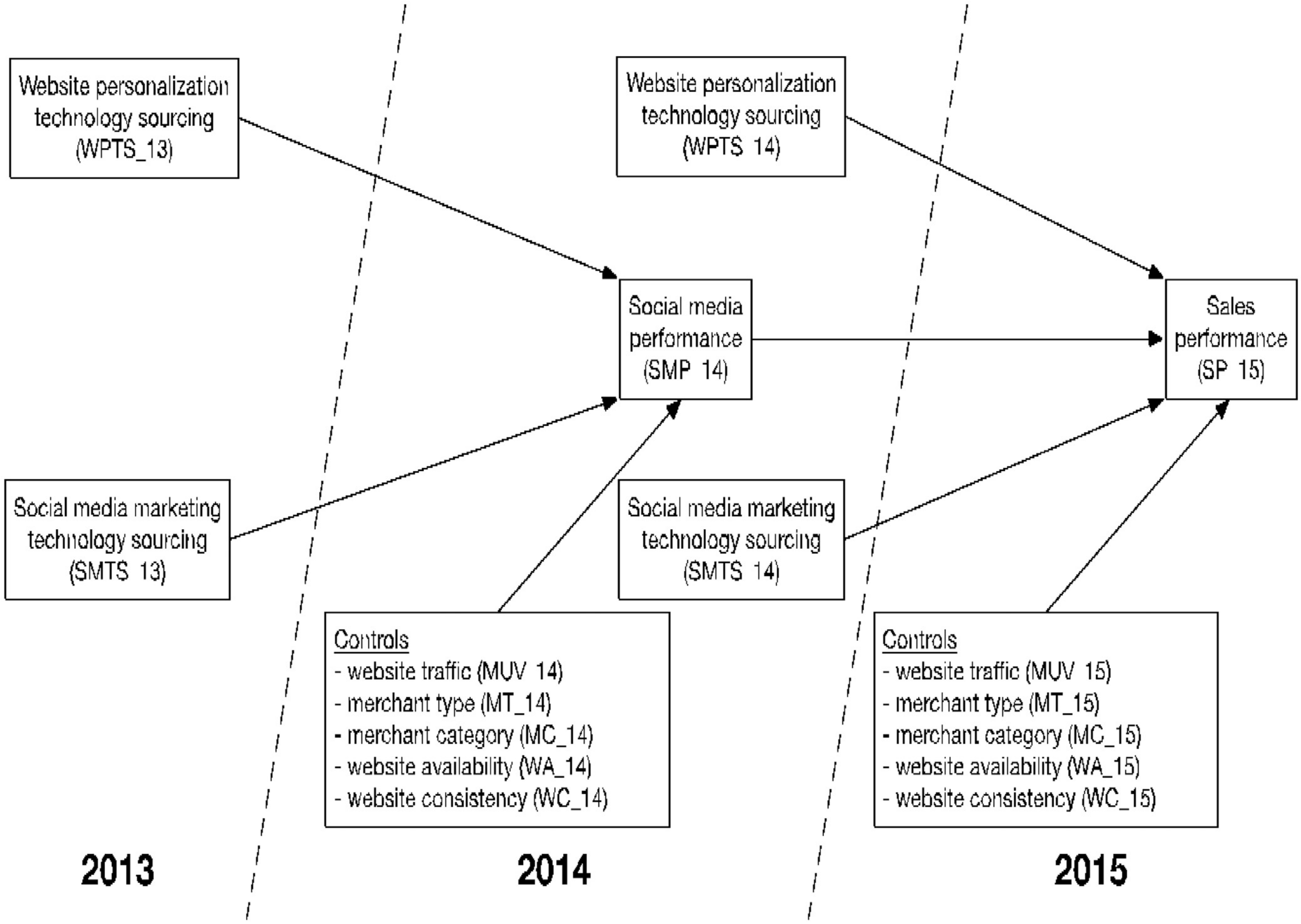

Fig. 2. Temporality of data.

Although every edition of the guide lists 500 e-retailers, the rankings change from one year to the next. Moreover, not all the measures are available for every e-retailer. For these two reasons, our final dataset is comprised of 105 e-retailers. We used two approaches to compare our final sample with the full dataset for the year 2015 (2016 edition), and assess whether the dataset reduction due to missing data could possibly affect our results.

First, we compared the distribution of variables across datasets. We performed a series of five Kolmogorov-Smirnov tests in the case of continuous variables and another series of nine Chi-square tests for categorical variables. Only the distribution of sales performance (SP_15) is significantly different across the two datasets ($p = 0.004$). As illustrated by Fig. 3, the mean and the standard deviation of sales performance is slightly greater in the final data (M = 8.395; S.D. = 0.634) than in the 2015 full data (M = 8.155; S.D. = 0.570). Although significantly different, some consistency across these two distributions can be noted.

Second, we explored whether the relationships between the variables were different in our final dataset. A Pearson correlation coefficient was calculated for each pair of continuous variables. For every pair of categorical variables, we calculated Cramér's *V*—a Pearson *r*-equivalent measure of association—that can only take positive values. Finally, we calculated eta squared for every association between a categorical and a continuous variable. Etas squared were then transformed into Cohen's *ds* (Cohen, 1988), and then *ds* were transformed into Pearson *rs* (Rosenthal, 1994). Because of this procedure, these *rs* between categorical and continuous variables can also take only positive values. This way, we created two correlation matrices, one for the final dataset and another for the complete dataset. We then estimated a series of Jennrich (1970) tests to compare these two correlation matrices. While every correlation in the final data correlation matrix has a sample size, $n = 105$, that is not the case in the complete dataset where the sample size across correlations ranges from 151 to 500. The Jennrich test, however, requires a constant sample size for each matrix. To get around this issue, we performed the test 19 times. First, we set n at 151 for the complete dataset, then we set it at 160 and increased this value by steps of 20 until it reached $n = 500$. None of these tests supports the hypothesis of a difference between the correlation matrices. Taken together, these results lead us to trust that the data reduction phenomenon due to case-wise deletion of incomplete observations is not worrisome.

In Table 1, we present an overview of our conceptual variables and operational measures. Tables 2 and 3 show descriptive statistics of our variables. The correlation matrix of the final dataset is presented in Table 4. The 95% confidence interval limits were obtained by bootstrapping (5000 replications) and are free of bias.

3.2. Measures

We use objective measures that have already been used in the extant literature to establish face and construct validity for all the variables. The data for all the measures used in this study was obtained from the

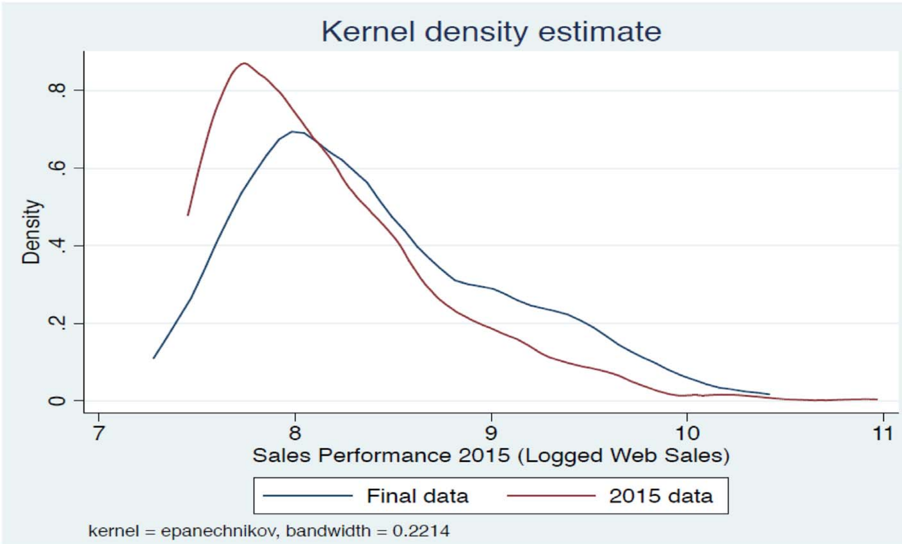

Fig. 3. Distribution of sales performance.

Internet Retailer Top 500 Guide (Editions 2014, 2015 and 2016). The publisher of this guide, Vertical Web Media, obtained this data through surveys of U.S. e-retailers. This survey data is complemented with information on two variables—website availability and website consistency—from Gomez.com, which evaluates website performance. This information from Gomez.com is compiled in the Internet Retailer Top 500 Guide. The measures of our key variables are provided below.

3.2.1. Sales performance (SP)

We measure our dependent variable as the logarithm of web sales

Table 2
Summary of continuous variables (n = 105).

Variable	Mean	Std. dev.	Min	Max
SMP_14	0.063	0.921	− 2.652	2.010
MUV_14	14.525	1.243	11.180	16.991
WA_14	0.997	0.007	0.966	1.000
SP_15	8.395	0.634	7.498	10.196
MUV_15	12.295	4.315	4.786	17.910
WA_15	0.995	0.013	0.907	1.000
WC_15	2.487	1.474	0.530	10.400

Table 1
Summary of measures.

Conceptual variable	Abbreviation	Operational measure
Sales performance	SP_15	Logarithm of Web sales for e-retailer in 2015.
Social media performance	SMP_14	Factor score from principal component analysis of ‘No. of + 1 s’ (Google Plus), ‘No. of likes’ (Facebook), ‘No. of Twitter followers’, ‘No. of Pinterest followers’, and ‘No. of Instagram followers’, all measured in 2014.
Technology sourcing for website personalization	$WPTS_i$_13 $WPTS_i$_14	Categorization of technology sourcing for website personalization in 2013 ($WPTS_i$_13) and 2014 ($WPTS_i$_14). i = 1, 2, 3. 1. Externally developed website personalization technology; 2. Mixed website personalization technology sourcing; 3. Internally developed website personalization technology.
Technology sourcing for social media marketing	$SMTS_j$_13 $SMTS_j$_14	Categorization of technology sourcing for social media marketing in 2013 ($SMTS_j$_13) and 2014 ($SMTS_j$_14). j = 1, 2, 3. 1. Externally developed social media marketing technology; 2. Mixed social media marketing technology sourcing; 3. Internally developed social media marketing technology.
Website traffic	MUV_14 MUV_15	Logged number of monthly unique visitors in 2014 (MUV_14) and 2015 (MUV_15).
Merchant type	MT_k_14 MT_k_15	The retailers in the dataset fall into 4 mutually exclusive categories describing their type (k): 1. Catalog/Call center; 2. Consumer-brand manufacturer; 3. Retail chain; 4. Web-only merchant. A dummy variable has been created for each category, in 2014 (MT_k_14) and 2015 (MT_k_15). For example, if MT_1_14 has a value of 1 it means that the corresponding e-retailer belongs to the ‘Catalog/Call center’ category in 2014.
Merchant category	MC_L_14 MC_L_15	The retailers in the dataset fall into 15 mutually exclusive categories based on their assortment (l): 1. Apparel/Accessories; 2. Automotive parts/Accessories; 3. Books/Music/Video; 4. Computers/Electronics; 5. Flowers/Gifts; 6. Food/Drug; 7. Hardware/Home improvement; 8. Health/Beauty; 9. Housewares/Home furnishings; 10. Jewelry; 11. Mass merchant; 12.Office Supplies; 13. Specialty; 14. Sporting Goods; 15. Toys/Hobbies. A dummy variable has been created for each category, in 2014 (MC_L_14) and 2015 (MC_L_15). For example, if MC_1_14 has a value of 1 it means that the corresponding e-retailer's assortment is made of ‘Apparel/Accessories’ in 2014.
Website availability	WA_14 WA_15	Percentage of time period out of a total of 8760 h (or 365 days) during which the system could be accessed in 2014 (WA_14) and 2015 (WA_15). Values range from 0 to 100.
Website consistency	WC_m_14 WC_15	The consistency the response times of successful site load tests. In 2014, the measure is categorical with 4 levels (m): 1. Poor; 2. Fair; 3. Good; 4. Excellent. A dummy variable has been created for each category (WC_m_14). For example, if the value of WC_1_14 is 1, it means that the consistency of the corresponding e-retailer's website in 2014 is categorized as ‘Poor’. In 2015 (WC_15), the measure is the standard deviation of the response times of successful site load tests. A lower number indicates a more consistent response time each time a user visits a website.

Table 3
Frequencies of categorical variables (n = 105).

Year	2013	2014	2015
Variable	WPTS_13	WPTS_14	
Externally developed technology	74	73	
Mixed technology sourcing	9	14	
Internally developed technology	22	18	
Variable	SMTS_13	SMTS_14	
Externally developed technology	42	42	
Mixed technology sourcing	26	27	
Internally developed technology	37	36	
Variable		MC_14	MC_15
Apparel/Accessories		30	32
Automotive parts/Accessories		2	2
Books/Music/Video		2	2
Computers/Electronics		8	8
Flowers/Gifts		4	5
Food/Drug		4	4
Hardware/Home improvement		3	3
Health/Beauty		8	7
Mass merchant		12	11
Housewares/Home furnishing		11	11
Jewelry		6	7
Office supplies		4	4
Specialty		7	4
Sporting goods		3	4
Toys/hobbies		1	1
Variable		MT_14	MT_15
Catalog/Call center		13	13
Consumer brand manufacturer		9	9
Retail chain		46	46
Web only		37	37
Variable		WC_14	
Poor		85	
Fair		12	
Good		4	
Excellent		4	

for each e-retailer in our sample. The distribution of the dependent variable had a positive skew, and hence in line with past studies (see for e.g., Duan, Gu, & Whinston, 2008) we use log transformation. Log transformation made the positively-skewed distribution more normal. The data on web sales in 2015 was obtained directly from the e-retailers through a survey conducted by the publishers of Internet Retailer Top 500 Guide.

3.2.2. Social media performance (SMP)

The survey data from Internet Retailer Top 500 Guide contains several metrics of social media performance (Andzulis, Panagopoulos, & Rapp, 2012; Murdough, 2009). For each e-retailer, we have the number of '+1 s' (Google Plus), number of 'Likes' (Facebook), and the numbers of Twitter, Instagram and Pinterest followers. These metrics being count data, we log-transformed them. Then, in an attempt to summarize these metrics in a unique measure of social media performance, we use the factor score from a factor analysis. A single-factor solution is retained since only one factor has an eigenvalue > 1 ($\lambda = 3.655$), the factor explains 73.11% of the original variance, and the five variables have satisfactory communalities (min $h = 0.603$).

3.2.3. Technology sourcing for website personalization ($WPTS_i$)

The survey conducted by publishers of Internet Retailer Top 500 Guide required e-retailers to clearly state whether the data mining technologies for WP (such as artificial neural networks, genetic algorithms, etc.) were developed by the e-retailer internally and/or externally. If the e-retailer sourced the data mining technology entirely or partly from external vendor(s), then they provided the name(s) of these vendor(s). In line with Patel (2014), we used this survey data to create a categorical measure for technology sourcing for WP with values 1, 2, and 3. Value 1 indicates that the e-retailer in our sample used only externally developed technologies for data mining, value 2 is used when the e-retailer obtains the data mining technologies from mixed sources (both internally developed and externally sourced technologies), and value 3 is provided for the use of fully internally developed data mining technologies. Our categorical measure thus indicates whether the core technological component of WP, namely data mining technology was developed internally and/or externally. Our measure does not capture technology sourcing for complementary technological components of WP like storage systems, or peripheral technological components like security software. Further, our measure does not include core non-technological components of WP like data and so does not take into consideration as to whether the firm's WP application uses only external data from users or if it combines this user data with the firm's internal data. Instead, our measure focuses on the core technological component of WP, namely data mining since it is required to provide e-retailing WP functions such as individualized price quotes, individualized search results, individualized advertisements or promotions based on the user's browsing history (Hauser et al., 2009; McFarland et al., 2006). In the paragraph below, we provide examples to show how we used this survey data to create a categorical measure of technology sourcing for WP.

In 2014, Target Corp. obtained part of the core components for WP from the company 'RichRelevance' and developed other core components internally. By doing so, Target Corp. opted for mixed technology sourcing, whereas Wayfair LLC opted to develop core technological components for WP internally, and HSN Inc. preferred to externally source core components for WP from 'Certona', 'MyBuys' and 'Monetate'.

3.2.4. Technology sourcing for social media marketing ($SMTS_i$)

The survey conducted by the publishers of Internet Retailer Top 500 Guide required e-retailers to clearly state whether the creative services activities, customer database management and network analysis technologies for SMM (such as nodal networks and algorithms) were developed by the e-retailer internally or externally. If the e-retailer sourced these technologies entirely or partly from external vendor(s), then they provided the name(s) of these vendor(s). In line with Patel (2014), we used this survey data to create a categorical measure for technology sourcing for SMM with values 1, 2, and 3. Value 1 indicates that the e-retailer in our sample used only external vendors for creative services activities, customer database management and network analysis technologies for SMM, value 2 is used when the e-retailer obtains these from mixed sources (both internally developed and externally sourced technologies), and value 3 is provided for the use of full internally-developed creative services activities, customer database management and network analysis technologies for SMM. Our measure does not capture technology sourcing for complementary technological components of SMM like the architecture of the social media site, or peripheral technological components like privacy-enabling technologies. Furthermore, our measure does not include core non-technological components of SMM like data, and so does not consider whether the firm's SMM application uses only external data from users or if it combines this user data with the firm's internal data. Instead, our measure focuses on the core technological components of SMM, namely creative services activities, customer database management and network analysis since it is required to provide social media functions such as promoting, sharing, co-creating, and discussing (Kietzmann et al., 2011). In the paragraph below, we explain (with the help of examples) how we used this survey data to create a categorical measure of technology sourcing for SMM.

Table 4
Correlations and 95% bootstrap-based bias-corrected confidence intervals (n = 105).

	SMP_14	WA_14	SP_15	WA_15	WC_15	WPTS_13	SMTS_13	WPTS_14	SMTS_14	MC_14	MT_14	WC_14	MC_15	MT_15	MUV_14
WA_14	− 0.096 [− 0.289, 0.149]														
SP_15	0.531 [0.392, 0.637]	− 0.034 [− 0.228, 0.168]													
WA_15	0.039 [− 0.151, 0.225]	− 0.007 [− 0.081, 0.108]	0.060 [− 0.085, 0.186]												
WC_15	0.056 [− 0.077, 0.179]	0.065 [− 0.093, 0.181]	− 0.072 [− 0.285, 0.141]	− 0.122 [− 0.439, 0.109]											
WPTS_13	0.409 [0.223, 0.541]	0.137 [0.065, 0.182]	0.361 [0.170, 0.513]	0.160 [0.073, 0.348]	0.125 [0.008, 0.230]										
SMTS_13	0.502 [0.345, 0.628]	0.041 [0.002, 0.067]	0.328 [0.154, 0.452]	0.093 [0.006, 0.140]	0.030 [0.002, 0.038]	0.324 [0.175, 0.435]									
WPTS_14	0.372 [0.169, 0.523]	0.088 [0.002, 0.171]	0.302 [0.108, 0.455]	0.083 [0.001, 0.161]	0.168 [0.029, 0.282]	0.853 [0.749, 0.950]	0.291 [0.151, 0.388]								
SMTS_14	0.495 [0.328, 0.619]	0.057 [0.001, 0.096]	0.326 [0.156, 0.456]	0.124 [0.011, 0.184]	0.047 [0.003, 0.082]	0.304 [0.160, 0.413]	0.891 [0.813, 0.963]	0.299 [0.157, 0.401]							
MC_14	0.493 [0.332, 0.539]	0.320 [0.228, 0.347]	0.478 [0.328, 0.520]	0.289 [0.186, 0.310]	0.259 [0.190, 0.254]	0.372 [0.277, 0.393]	0.331 [0.277, 0.299]	0.342 [0.294, 0.324]	0.366 [0.287, 0.346]						
MT_14	0.504 [0.343, 0.612]	0.195 [0.061, 0.292]	0.255 [0.061, 0.373]	0.016 [0.003, 0.003]	0.154 [0.020, 0.236]	0.296 [0.161, 0.363]	0.301 [0.173, 0.368]	0.297 [0.175, 0.367]	0.271 [0.132, 0.342]	0.354 [0.308, 0.331]					
WC_14	0.152 [0.043, 0.251]	0.198 [0.065, 0.517]	0.071 [0.008, 0.102]	0.050 [0.004, 0.062]	0.208 [0.085, 0.298]	0.151 [0.054, 0.229]	0.214 [0.100, 0.271]	0.189 [0.078, 0.291]	0.214 [0.093, 0.271]	0.425 [0.199, 0.508]	0.151 [0.101, 0.157]				
MC_15	0.474 [0.312, 0.511]	0.307 [0.212, 0.341]	0.438 [0.292, 0.48]	0.359 [0.199, 0.497]	0.318 [0.183, 0.345]	0.350 [0.256, 0.362]	0.297 [0.243, 0.243]	0.326 [0.221, 0.311]	0.334 [0.289, 0.294]	0.948 [0.910, 0.980]	0.387 [0.342, 0.375]	0.443 [0.254, 0.527]			
MT_15	0.504 [0.353, 0.615]	0.195 [0.062, 0.294]	0.255 [0.056, 0.368]	0.016 [0.003, 0.003]	0.154 [0.019, 0.237]	0.296 [0.169, 0.365]	0.301 [0.168, 0.369]	0.297 [0.127, 0.360]	0.271 [0.123, 0.341]	0.354 [0.329, 0.340]	1.000 [1.00, 1.00]	0.151 [0.096, 0.156]	0.225 [0.200, 0.212]		
MUV_14	0.554 [0.428, 0.655]	0.039 [− 0.130, 0.189]	0.760 [0.655, 0.839]	0.050 [− 0.070, 0.178]	− 0.109 [− 0.332, 0.098]	0.203 [0.023, 0.361]	0.175 [0.018, 0.312]	0.200 [0.025, 0.360]	0.177 [0.022, 0.313]	0.593 [0.385, 0.659]	0.288 [0.080, 0.413]	0.110 [0.009, 0.178]	0.567 [0.386, 0.626]	0.288 [0.104, 0.423]	
MUV_15	0.555 [0.414, 0.668]	0.013 [− 0.168, 0.214]	0.641 [0.533, 0.729]	0.053 [− 0.107, 0.237]	− 0.181 [− 0.398, 0.021]	0.211 [0.027, 0.373]	0.267 [0.074, 0.416]	0.194 [0.027, 0.359]	0.260 [0.062, 0.414]	0.521 [0.347, 0.551]	0.220 [0.038, 0.346]	0.142 [0.009, 0.215]	0.499 [0.380, 0.543]	0.220 [0.038, 0.345]	0.874 [0.834, 0.905]

In 2014, Dell Inc. sourced the core components for SMM from ‘Gigya’ and ‘Poptent’ and hence opted to use externally developed technologies. Staples Inc. used mixed technology sourcing for SMM. It obtained part of the core components for SMM technologies from the company ‘Kenshoo’ and developed other core components internally. Overstock.com Inc. opted to fully develop core technological components for SMM internally.

3.2.5. Control variables

Both sales performance and social media performance likely depend on other firm-related variables. First, we control for lagged *website traffic* by including the logarithm of number of monthly unique visitors (*MUV*) of the previous year, as it seems likely that sales and social media performance increase with the number of visitors. We think that the number of visitors also captures lagged market performance and thus helps to control for omitted variable bias in our models.

Second, performance may depend on the e-retailer category and type (Lilien & Yoon, 1990). We control for dummy variables capturing the type of *merchandise category* (MC_l) and also control for dummy variables capturing the *type of merchant* (MT_k).

In addition, we consider as controls certain website technical performance metrics, namely *website availability* (*WA*) and *website consistency* (*WC*), which might affect our dependent variable (Anderson, Fornell, & Lehmann, 1994). Website availability is the ability of the user community to access the system, either for the purpose of obtaining goods or services, or to access existing information. If a user cannot access the system, then the website is considered as being unavailable. We measure website availability as the percentage of time period out of a total of 8760 h (or 365 days) during which the system can be accessed in a given year. The values of website availability range from 0 to 100%, such that 99.9% availability implies that the system can be accessed for 8751 h out of 8760 h per non-leap year, but it will be inaccessible for 9 h. Website consistency is the time taken by users for completing transactions on the website. The 2014 measure of website consistency (WC_m_14) is an ordinal variable that specifies the relative range of response time for completing a transaction on the website (from 1 = Poor to 4 = Excellent). Poor website consistency as indicated by value of 1 implies that the range of response time is large. Meanwhile, excellent website consistency as indicated by value of 4 implies that the range of response time is small. Website consistency in 2015 (*WC*_15) was measured as the standard deviation of the response time of successful site load tests. This measure gives a continuous score, wherein a lower number indicates a more consistent response time when a user visits a website. The measurements for website availability and consistency were obtained from Gomez.com and were compiled in the Internet Retailer Top 500 Guide.

4. Analyses and results

4.1. Model specification

Following Gatignon's (2014) recommendations, we estimate our model using mediated regression. This approach involves two steps. Firstly, Seemingly Unrelated Regression (SUR) is used to simultaneously estimate two models (Eqs. (1) and (2)). In Eq. (1), social media performance (t = 2014) is regressed on the two technology sourcing variables (t = 2013) and the control variables (t = 2014). In Eq. (2), sales performance (t = 2015) is regressed on social media performance (t = 2014), the two technology sourcing variables (t = 2014) and the control variables (t = 2015). Then, the indirect effects of technology sourcing decisions on sales performance through social media performance are estimated and tested. Note that we chose SUR instead of a structural equation model (SEM) because SEM is unable to model multiple categorical variables in a practical manner (Bollen, 1989).

System of equations

$$\begin{aligned}\mathrm{SMP}_{14} = \beta_{10} &+ \sum_{i=2}^{3} \beta_{11_i} WPTS_i 13 \\ &+ \sum_{j=2}^{3} \beta_{12_j} SMTS_j 13 \\ &+ \sum_{k=2}^{4} \beta_{14_k} MT_k \\ 14 &+ \sum_{l=2}^{15} \beta_{15_l} MC_l 14 + \beta_{16} WA_{14} + \sum_{m=2}^{4} \beta_{17_m} WC_{m14} + \beta_{18} MUV_{14}\end{aligned} \tag{1}$$

$$\begin{aligned}\mathrm{SP}_{15} = \beta_{20} &+ \sum_{i=2}^{3} \beta_{21_i} WPTS_{i14} + \sum_{j=2}^{3} \beta_{22_j} SMTS_{j14} + \beta_{23} SMP_{14} \\ &+ \sum_{k=2}^{4} \beta_{24_k} MT_{k15} + \sum_{l=2}^{15} \beta_{25_l} MC_{l15} + \beta_{26} WA_{15} + \beta_{27} WC_{15} + \beta_{28} MUV_{15}\end{aligned} \tag{2}$$

4.2. Modeling challenges

The equations above require us to model the effect of technology sourcing decisions on firm performance variables. This raises some econometric issues because firms might self-select to use technology that has been developed internally or externally based on unobserved firm specific factors like their internal capabilities. Therefore, the independent sourcing variables of such a model could be potentially endogenous and correlated with the error term. If we do not account for the effect of these unobserved variables, our model would suffer from omitted variable bias and the coefficients would be biased (Hamilton & Nickerson, 2003).

We check for endogeneity of WPTS and SMTS using an instrumental variables estimator (Stock & Watson, 2003). Specifically, we used lagged WPTS and SMTS as instrumental variables in place of the potentially endogenous variables. We performed instrumental variable estimations of Eqs. (1) and (2) using these instruments, and then conducted the test of endogeneity for the regressors (i.e. WPTS and SMTS). The endogeneity test statistic was not significant (χ^2 = 9.82, p = 0.13 for eq. 1; χ^2 = 2.23, p = 0.89 for Eq. (2)), so our technology sourcing variables are not endogenous. Because this test result is sensitive to the reliability and validity of the instruments used, we also conducted several further tests. To check the validity of both instruments, we conducted the Sargan-Hansen test of over-identifying restrictions for each instrument and for both Eqs. (1) and (2). The Hansen's J statistic was not significant ($p > 0.1$) for either lagged WPTS or lagged SMTS, which indicated that the instruments are valid and uncorrelated with the error term in Eqs. (1) and (2) (Hayashi, 2000). To check for the reliability of lagged WPTS and lagged SMTS as instruments, we conducted a test of weak correlation of these instruments with the potential endogenous regressors. Specifically, we estimate the Cragg and Donald (1993) minimum eigenvalue statistic, which we then used to infer the degree to which the instrumental variable estimate is biased and the degree of the size distortion relative to the OLS estimate. As per Stock and Yogo's (2005) suggestions, the value of the eigenvalue statistic for both our instruments in Eqs. (1) and (2) indicates that the bias and the size distortion resulting from the use of the instruments was < 5% of the bias from the OLS estimate and the size distortion was < 10% of the OLS estimate. This implies that the instruments are not weakly correlated with our technology-sourcing variables and we can conclude that these variables are not endogenous. In the absence of endogeneity, we estimated Eqs. (1) and (2) using SUR. The parameter estimates and tests from the SUR estimation are reported in Table 5. Consistent with the specific nature of the hypothesized effects, reported p-values are for one-tailed tests and confidence intervals are calculated accordingly for a 90% level of confidence. We discuss the results of this estimation and implications for our hypotheses below.

Table 5
Parameter estimates.

	Dependent variable: SMP_14 (R^2 = 0.765)						Dependent variable: SP_15 (R^2 = 0.634)				
	Coef.	Std. err.	z	P > z[a]	90% CI		Coef.	Std. err.	z	P > z	90% CI
Intercept	1.985	7.459	0.27	0.790	[−10.284, 14.254]	Intercept	7.086	3.040	2.33	0.010	[2.086, 12.086]
						SMP_14	0.401	0.074	5.42	0.000	[0.279, 0.523]
WPTS_13[b]						WPTS_14[b]					
External Sourcing	−0.464	0.180	−2.58	0.005	[−0.760, −0.168]		−0.350	0.122	−2.87	0.002	[−0.550, −0.149]
Internal sourcing	−0.585	0.209	−2.80	0.003	[−0.928, −0.242]		−0.402	0.158	−2.54	0.006	[−0.663, −0.142]
SMTS_13[c]						SMTS_14[c]					
Mixed Sourcing	−0.385	0.125	−3.07	0.001	[−0.591, −0.178]		−0.090	0.109	−0.82	0.206	[−0.269, 0.090]
Internal sourcing	−0.649	0.126	−5.14	0.000	[−0.857, −0.441]		−0.027	0.116	−0.24	0.407	[−0.219, 0.164]
Control variables											
MUV_14	0.425	0.047	9.06	0.000	[0.348, 0.503]	MUV_15	0.043	0.013	3.32	0.000	[0.022, 0.064]
MT_14[d]						MT_15[d]					
Consumer brand manufacturer	0.754	0.208	3.62	0.000	[0.411, 1.096]		−0.292	0.182	−1.60	0.055	[−0.592, 0.008]
Retail chain	0.178	0.174	1.02	0.153	[−0.108, 0.463]		−0.115	0.141	−0.82	0.207	[−0.347, 0.116]
Web only	−0.235	0.170	−1.38	0.084	[−0.514, 0.045]		−0.038	0.145	−0.27	0.396	[−0.277, 0.200]
MC_14[e]						MC_15[e]					
Automotive parts/accessories	−1.007	0.330	−3.05	0.001	[−1.550, −0.464]		0.586	0.292	2.01	0.023	[0.105, 1.067]
Books/music/video	0.537	0.338	1.59	0.056	[−0.019, 0.1.094]		−0.409	0.286	−1.43	0.075	[−0.880, 0.062]
Computers/electronics	−0.789	0.196	−4.02	0.000	[−1.112, −0.467]		0.651	0.168	3.88	0.000	[0.375, 0.927]
Flowers/gifts	−0.682	0.261	−2.61	0.005	[−1.111, −0.252]		0.102	0.204	0.50	0.308	[−0.233, 0.437]
Food/drug	0.148	0.268	0.55	0.291	[−0.292, 0.588]		0.427	0.213	2.01	0.023	[0.077, 0.777]
Hardware/home improvement	−0.169	0.283	−0.60	0.276	[−0.635, 0.297]		0.667	0.233	2.86	0.002	[0.284, 1.050]
Health/beauty	0.487	0.187	2.60	0.005	[0.179, 0.795]		−0.015	0.170	−0.09	0.465	[−0.295, 0.265]
Housewares/home furnishing	−0.442	0.168	−2.63	0.004	[−0.719, −0.166]		0.413	0.147	2.80	0.003	[0.170, 0.655]
Jewelry	0.072	0.217	0.33	0.370	[−0.285, 0.430]		0.241	0.171	1.41	0.077	[−0.040, 0.523]
Mass merchant	−0.583	0.171	−3.42	0.000	[−0.863, −0.302]		0.223	0.143	1.57	0.059	[−0.011, 0.458]
Office supplies	−1.102	0.250	−4.40	0.000	[−1.513, −0.690]		0.943	0.215	4.38	0.000	[0.589, 1.297]
Specialty	−0.496	0.197	−2.52	0.006	[−0.819, −0.172]		0.361	0.227	1.59	0.056	[−0.012, 0.735]
Sporting goods	−0.244	0.286	−0.86	0.196	[−0.714, 0.226]		0.023	0.215	0.11	0.458	[−0.330, 0.376]
Toys/hobbies	−0.048	0.566	−0.08	0.467	[−0.980, 0.884]		0.450	0.400	1.13	0.130	[−0.208, 1.108]
WA_14	−7.148	7.463	−0.96	0.169	[−19.423, 5.127]	WA_15	1.025	3.044	0.34	0.368	[−3.982, 6.032]
WC_14[f]						WC_15	−0.024	0.028	−0.86	0.195	[−0.071, 0.022]
Fair	0.020	0.151	0.13	0.447	[−0.229, 0.269]						
Good	−0.262	0.307	−0.85	0.197	[−0.767, 0.243]						
Excellent	−0.159	0.250	−0.64	0.263	[−0.569, 0.252]						

[a] One-tailed.
[b] Reference category is 'Mixed Sourcing'.
[c] Reference category is 'External Sourcing'.
[d] Reference category is 'Catalog/Call center'.
[e] Reference category is 'Apparel/Accessories'.
[f] Reference category is 'Poor'.

4.3. Hypotheses tests

4.3.1. Effects of website personalization technology sourcing

When the dependent variable is sales performance, both the effects of the dummy variables corresponding to externally and internally developed WP technology are negative and significant ($\beta = -0.350$, $p = 0.002$ and $\beta = -0.402$, $p = 0.006$, respectively). This shows that the sales performance associated with these sourcing decisions is significantly lower than the one associated with the reference category in the dummy coding scheme for WP technology sourcing, i.e. mixed technology sourcing. Hypothesis H1a is thus supported.

When social media performance is the dependent variable, both the effects of the dummy variables corresponding to externally and internally developed WP technology are negative and significant ($\beta = -0.464$, $p = 0.005$ and $\beta = -0.585$, $p = 0.003$, respectively). This shows that the level of social media performance associated to these sourcing decisions are significantly lower than the one associated with the reference category in the dummy coding scheme for WP technology sourcing, i.e. mixed technology sourcing. Hypothesis H1b is thus supported.

4.3.2. Effects of social media marketing technology sourcing

On the one hand, the results show that social media performance is significantly lower when mixed technology sourcing is used ($\beta = -0.385$, $p = 0.001$) or when internally developed technology is used ($\beta = -0.649$, $p = 0.000$) for SMM than when externally developed technology is used, thus supporting hypothesis H2a. On the other hand, no significant difference in terms of sales performance is observed between mixed technology sourcing and externally developed technology for SMM ($\beta = -0.090$, $p = 0.206$), nor between internally and externally developed technology ($\beta = -0.027$, $p = 0.407$). Consequently, hypothesis H2b is not supported.

4.3.3. Effect of social media performance on sales performance

The effect of social media performance on sales performance is significant and positive ($\beta = 0.401$, $p = 0.000$). Hypothesis H3 is thus supported.

4.4. Further examination of indirect effects

Since our hypotheses deal, on the one hand, with the effects of technology sourcing decisions on social media performance and, on the other hand, with the effect of social media performance on sales performance, we performed additional tests for the indirect (i.e. mediated) effects of sourcing decisions on sales performance. First, the indirect effects are calculated by multiplying the coefficients corresponding to the effects of sourcing decisions on social media performance with the coefficient corresponding to the effect of social media performance on sales performance. Then a bootstrapping procedure (5000 replications) is used to calculate the confidence intervals of these coefficient

Table 6
Effects of technology sourcing decisions on sales performance, direct and indirect through social media performance.

	Direct effects				Indirect effects			
	Coef.	Bias	Boostrap s.e.	90% bias corrected CI	Coef.	Bias	Boostrap s.e.	90% bias corrected CI
	Website personalization technology sourcing[a]							
External	− 0.350	− 0.013	0.138	[− 0.559, − 0.100]	− 0.186	0.004	0.097	[− 0.383, − 0.058]
Internal	− 0.402	− 0.015	0.201	[− 0.724, − 0.068]	− 0.235	0.009	0.114	[− 0.454, − 0.079]
	Social media marketing technology sourcing[b]							
Mixed	− 0.090	− 0.006	0.154	[− 0.333, 0.172]	− 0.154	− 0.002	0.074	[− 0.303, − 0.056]
Internal	− 0.027	0.015	0.131	[− 0.271, 0.164]	− 0.260	− 0.006	0.087	[− 0.419, − 0.136]

[a] Reference category is 'Mixed Technology Sourcing'.
[b] Reference category is 'Externally Developed Technology'.

products, which is required to test for the significance of such indirect effects (Bollen & Stine, 1990; MacKinnon, Lockwood, & Williams, 2004). The bias-corrected confidence intervals for the indirect effects are reported in Table 6. We also report the bootstrapped direct effects as robustness checks of the results discussed in the previous section and to allow a full interpretation of both direct and indirect effects.

The indirect effect of mixed technology sourcing for WP through social media performance leads to significantly greater sales performance than when firms use externally developed technology (5.6% to 38.3% increase in sales)[9] or internally developed technology (7.9% to 45.4% increase in sales). The bootstrap results also show that the direct effect of a mixed technology sourcing for WP increases the sales by 10.0% to 55.9% compared to externally developed technology, and by 6.8% to 72.4% compared to internally developed technology. In sum, the increase in sales compared to externally developed technology is between 15.6% and 94.2%, and between 14.7% and 117.8% compared to internally developed technology (direct and indirect effects). Consequently, the combination of direct and indirect effects of WP technology sourcing decision clearly reinforces the conclusion that mixed technology sourcing is the best option.

Finally, the indirect effect of externally developed SMM technology through social media performance leads to significantly higher levels of sales performance, compared to mixed technology sourcing (5.6% to 30.3% increase in sales) and to internally developed technology (13.6% to 41.9% increase in sales). This is consistent with our conclusions regarding H2a and H3. The direct effect of SMM technology sourcing on sales performance (H2b) was not supported. However, our results show an effect of technology sourcing decisions regarding SMM on sales performance that is fully mediated by social media performance. Therefore, we can conclude that externally developed technology for SMM is the best option since it positively affects sales performance, although indirectly, through social media performance.

5. Discussion and implications

5.1. Implications for research

Our study makes several theoretical contributions to the continuing discussion on technology sourcing by suggesting that e-retailers need different technology sourcing approach across WP and SMM. First, our theoretical framework reveals the mechanism by which different technology sourcing options for WP have different effects on sales performance of e-retailers. The differences in the effects are explained using the concepts of efficiency and adaptability (Weigelt & Sarkar, 2012), asset-specificity (Williamson, 1985), risks of dependency and lack of quality control (Huang et al., 2004; Ye et al., 2014). Specifically, we argue that the choice of mixed technology sourcing for WP will increase efficiency, adaptability and absorptive capacity for e-retailers.

Second, our theoretical framework also illustrates the mechanism by which technology sourcing options for SMM affects sales performance of e-retailers by using the concepts of efficiency and tacit knowledge. Extant literature on the technology sourcing decision for SMM is very limited. We contribute to this literature by arguing that using externally developed technology for SMM increases efficiency, and provides critical expertise to e-retailers such as creative services, customer database management, network analysis skills and knowledge (Alfaro & Watson-Manheim, 2015; Groza et al., 2012).

5.2. Implications for practice

First, our results suggest that firms should opt for mixed technology sourcing for WP. Such firms are likely to have greater sales relative to firms that use either internally or externally developed technology. Choosing externally developed technology may appear to be the faster and cheaper route to WP. However, opting for an existing market solution is likely to lead to very generic and standardized WP that will not provide any competitive advantage to the e-retailer. In-house technology development will be resource intensive and constraining. Moreover, in-house development of technology can result in core rigidities.

Second, there is little guidance in prior literature on best practices for technology sourcing for SMM. We advise that firms should adopt externally developed technology for SMM. Such firms are likely to have greater social media performance and greater sales relative to firms that use either internally developed technology or mixed technology sourcing. Opting for internally developed technology may seem appealing as SMM can be integrated with the overall marketing strategy of the firm. However, managers lack critical expertise to function efficiently on the diverse social media platforms. Mixed technology sourcing is unlikely to resolve efficiency and expertise related issues resulting from use of internally developed SMM.

Third, existing literature does not link a firm's social media performance directly to a firm's sales performance. Extant literature explored the impact of social media on sales force and automation of sales force (Rodriguez et al., 2012). The past literature has also studied the relationship between a firm's presence on social media and its impact on sales performance (Du & Jiang, 2014). We recommend that firms should improve their social media performance. Firms with greater social media performance are likely to have greater sales performance.

6. Limitations and suggestions for further research

Our study has several conceptual and empirical limitations. First, our study uses secondary data published by Vertical Web Media in the Internet Retailer Top 500 Guide. We preferred to use this data instead of collecting primary data from e-retailers for various reasons. Vertical

[9] Since sales were log-transformed, our model is a log-level regression model. Consequently, the coefficients must be interpreted as a percentage of change in sales for a one-unit change in the independent variable, which in the case of a dummy-coded categorical independent variable corresponds to the difference between the two categories under study.

Web Media has conducted annual surveys of e-retailers in the U.S. since 2003. Despite annual efforts by Vertical Web Media, only 105 from 500 top e-retailers provide all the data required by us. Moreover, as explained in detail in Section 3.1 Empirical context and sample, we did tests with objective to assess whether the dataset reduction due to missing data could possibly affect our results. Furthermore, having complete responses from 105 top e-retailers amounts to a 21% response rate. According to Baruch and Holtom (2008) the average response rate for academic organizational studies that utilized data collected from organizations was 35.7% with a standard deviation of 18.8. Hence, the response rate of 21% of the survey conducted by Vertical Web Media from 500 top e-retailers could be considered adequate.

Second, we study sales performance and ignore other important performance measures, like profits. Our choice of dependent variable was somewhat constrained by the type of data to which we had access to. Nonetheless, considering sales performance as our main dependent variable was important because extant literature mainly focuses on intermediate outputs of technology sourcing (Fitoussi & Gurbaxani, 2012; Goo et al., 2009).

Third, our data is limited to the largest e-retailers ranked in-terms of web sales as per the Internet Retailer Guide, which raises questions about the applicability of our results to smaller e-retailers. Yet, it is noteworthy that our data is not describing a homogeneous group of e-retailers and offers substantial variance in terms of volume of turnover: the smallest e-retailer in our final dataset has a turnover of $31.5 million US dollars, which is 498 times less than that of the largest e-retailer. Howsoever that may be, further research should look across a broader size range of e-retailers and across other Internet-based channels like m-commerce to enhance the external validity and verify the generalizability of these results. Furthermore, we recognize that our data analysis approach can be complemented by other approaches to studying causal effects like the Bayesian approach.

To advance our findings, we call for research on WP and SMM that takes the stage of the industry life cycle into account. The technology sourcing decision might differ if the industry is undergoing initial development. For example, during the era of ferment or pre-dominant design stage, the industry is characterized by extreme technological uncertainty with intense competition among technology vendors to get their design of the innovation adopted by a majority of stakeholders within the industry as the standard or the dominant design. The technology sourcing decisions of e-retailers introducing WP or SMM under such uncertain conditions need further investigation. These points should be addressed in future research.

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