The Pursuit of Conversion: Effects of Mediating Channels on Product Choices and Purchase Propensities in Social Commerce Platforms

Completed Research Paper

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Abstract

This study elucidates the effectiveness of intermediary channels in driving sales at social commerce sites (SCSs). Using a panel data, we investigate how the external intermediary channels through which consumers arrive at SCSs influence product choice and purchase likelihood. In addition, we scrutinize the extent to which product categories with varying quality moderate the relationship between consumers' channel-related behaviors and purchase propensities. Furthermore, we examine how external channels "collaborate" with internal channels to increase purchase likelihood. The findings suggest that consumers who enter the SCS through direct apps and portals engage in more proactive purchasing than do consumers landing at the SCS via metasites or e-mail promotions. Consumers who are directed to the SCS through metasites or e-mail promotions are more likely to purchase experience goods than search goods. Contrary to previous findings, consumers' purchasing propensities decline, rather than increase, across all channels after the implementation of a recommendation system.

Keywords: social commerce, external mediating channels, purchase propensities, MCMC

Introduction

Social commerce sites (SCSs), such as Groupon and LivingSocial, have significantly evolved as legitimate players in electronic and mobile commerce markets, solidifying their presence in the marketplace by changing the nature of value propositions[1]. The social commerce frenzy has enabled these powerhouses to entrench themselves in online retail ecosystems that facilitate numerous heavily discounted transactions across diverse product categories. Retailers with a presence in daily deal social commerce platforms exchange margin for volume by selling their goods in bulk to shoppers who team up to avail of products at wholesale prices. This simple market coordination paradigm should result in a win-win situation, in which all participants benefit and share the economic rent.

The proliferation of mobile platforms that facilitate the convergence of collaborative, location-based, and on-the-go technologies has expedited the growth of social commerce. The revenues generated through these platforms account for nearly 50% of the sales in collective social venues[2]. This emerging daily deal paradigm perfectly aligns with a new e-commerce trend termed SoLoMo (short for social, local, and mobile), wherein online consumers shop socially, search locally, and conduct transactions through mobile devices. Empowered by the voguish SoLoMo, SCSs have become a hub for referral and affiliate programs. Many consumers land directly on social commerce platforms through mobile apps, but numerous other shoppers are enticed by alternative mediating channels to course their purchases through social commerce platforms. Mega-coupon sites, such as coupons.com and DealsPlus, for example, are new important external mediating channels through which consumers arrive and shop at SCSs; these sites collect and distribute a wide range of commercial coupons and deals that can be redeemed at SCSs. Portal sites, including external search engines, also continue to steer heavy traffic volume toward social commerce platforms. Promotional emails are other intermediaries that lure consumers to SCSs.

Although social commerce research is rapidly advancing in consonance with the increasing business ramifications of the mobile era, little is known about the economic value of mediating channels, particularly in the context of mobile social commerce. No significant effort has been extended to a systematic probing of how the diverse external intermediary channels through which consumers arrive at SCSs influence product choice and purchase likelihood. Do customers who are shepherded to SCSs through niche coupon sites hold higher purchase propensities than those who find these sites via search engines and other portal services? Similarly, are consumers who land at SCSs directly through mobile apps relatively more likely to purchase a product than those who are lured to SCSs via e-mail coupons?

In addition, to throw light on the aforementioned issues, we investigate how external mediating channels (e.g., portals, meta sites, and email promotions) "collaborate" in concert with SCSs' internal channels (e.g., a recommendation system run by the SCS) to increase purchase likelihood (Figure 1). Numerous consumers are ushered to SCSs through external referral channels, but many deal-hunters carry on this journey within internal channels once they land on the main page of an SCS. A particular internal channel accessed by consumers is the recommendation system by which lucrative alternatives are displayed. Little is known about whether consumers who directly enter SCSs are more likely to make a purchase through recommendation systems than are consumers who are escorted to SCSs through external mediating channels. This study aspires to illuminate these issues. To this end, we perform a field experiment as bases for examining changes in consumers' purchase behaviors in response to the institution of recommendation systems at a large SCS.

Finally, we scrutinize the extent to which product categories with extensively varying quality (i.e., experience and search attributes) (Nelson 1970) moderate the relationship between consumers' channel-related behaviors and purchase propensities. Compared with consumers who land on sites via e-mail promotions, for instance, are portal-directed customers more likely to purchase "experience goods" (e.g., travel goods) whose quality can be determined only after purchase? How does the situation change when

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[1] The definition of social commerce varies widely because it takes on divergent forms depending on business model. In this study, we focus exclusively on major social commerce platform providers such as Groupon and Living Social.

[2] http://www.chicagobusiness.com/article/20130608/ISSUE01/306089984/call-it-groupon-3-0-deals-giant-on-a-mobile-mission

the offer involves search products characterized by less quality uncertainty (e.g., clothing)? Investigating the moderating effect of quality uncertainty is particularly important in social commerce because information asymmetry, vendor opportunism, and other source of market friction have diminished the credibility of this sector and have prevented consumers from seamlessly purchasing goods. The market imperfection inherent in SCSs is further magnified because such daily deal venues typically impose time pressure on consumers, limiting deal availability to a short duration. Consequently, consumers who patronize these emergent outlets are often unable to complete their purchases because they contend with deal durations to which adherence is often impossible. Confronted by these structural challenges, SCS operators are searching for new avenues (e.g., referral sites and affiliate programs) by which to boost sales, as well as enhance the efficiency and effectiveness of their marketing campaigns. We assess the economic value of diverse mediating channels that structurally vary in terms of the operational mode implemented and the cognitive costs incurred in information processing (Johnson et al. 2003). For a more nuanced inquiry, we classify channels into two broad categories (memory- and stimulus-based channels) and investigate their effects on the purchase propensities moderated by the characteristics of products and the accessibility of internal channels (e.g., recommendation systems).

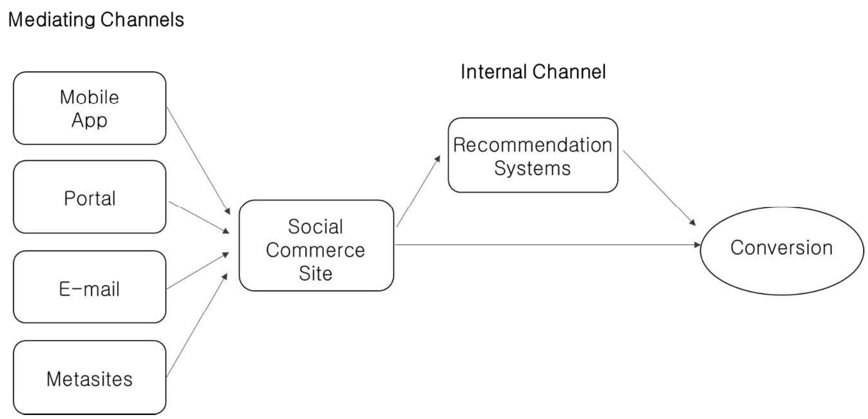

Figure 1. An illustration of external mediating and internal channels

Using a combination of field experiments and transactional panel data that describe the behavioral patterns of 15,439 consumers who subscribed to a major SCS during the study period, we investigate the effects of external mediating channels on purchase intent in social commerce spaces. We estimate individual utility analysis on the basis of 385,198 observations and 19,004 deals over the SCS. The computer IP address information included in the dataset enables us to monitor and analyze the unique individual behaviors of SCS consumers. These behaviors include the number of clicks on a particular product prior to purchase, the specific external mediating channel through which a consumer arrives at a given SCS, responses to diverse discount deals, the timing of purchases, and reliance on recommendation systems. We focus on six of the most popular categories on SCSs: fashion items, food, restaurants, home supplies, service, and travel products. These categories differ in terms of the level of quality uncertainty that consumers perceive in them prior to purchase, with travel goods regarded as the most uncertain. We employ a Bayesian Markov chain Monte Carlo (MCMC) technique, which allows us to stochastically estimate the individual propensity to purchase across the diverse mix of channels and product categories. The MCMC mechanism is suitable as our analytical strategy since consumers' preferences are highly diverse and dynamic in social commerce sites in which deals are short-lived and products' brand values are less recognized.

The remainder of the paper is organized as follows. In the next section, we discuss the theoretical framework guiding the development of the hypotheses. We then describe our panel data and model specifications in detail. The subsequent section presents our empirical findings on the effects of mediating channel choice on purchase propensities. Finally, we conclude with the implications of our study and possible directions for future research.

Theoretical Background and Hypotheses

Memory-based vs. Stimulus-based Online Channels

Memory is an essential faculty by which humans engage in decision-makings (Alba et al. 1991). When confronted with choice-determining situations, consumers often make *stimulus-based* decisions by leveraging the information available in a physical environment (e.g., grocery stores) (Biehal and Chakravarti 1983). Other consumers, however, opt to embark on *memory-based* decision-making that is grounded on the information retrieved from memory (Kardes 1986; Lee 2002). Consider a situation in which a consumer uses her memory as input in creating a shopping list that contains items to be purchased from a supermarket. Alternatively, the shopper can visit the store without such list and use certain purchase criteria (e.g., price, color, and discount) as bases in choosing items from an array of competing products displayed on selves at the point of purchase. The former strategy represents a memory-based decision-making process, whereas the latter is a stimulus-based mechanism. The key difference between the two modes is that while the memory-based mechanism is driven endogenously (internally by the consumer), the stimulus-based is determined exogenously (externally by the environment or stimuli). In this respect, the memory-based approach may entail intention-based actions (Hommel 2003).

Under a stimulus-based situation, the information required to carry out cognitive functions is readily available in a physical environment, but memory-based conditions lack such relevant information (Lee 2002; Lynch Jr and Srull 1982). The memory-stimulus framework may be applied to the analysis of choice in online environments. Some consumers are captivated by online display ads or promotional e-mails that feature attractive heavy discounts. Others, such as bargain hunters, are enticed by meta-coupon sites and list numerous available options to find the best deals. Consumers who use these deal-driven channels are stimulated by physically available information (e.g., low prices and promotional coupons)[3]. Conversely, shoppers can visit portal sites and enter specific keywords that are accessed from memory in a quest to locate products of interest. Similarly, mobile consumers may choose a particular retailer from many selections and activate its apps to initiate product searches, for which intended actions and subsequent cognitive procedures are involved. These activities entail memory-based, intention-driven courses of action because they require mental processing and information retrieval from memory. With this consideration in mind, we conceptualize a continuum that captures the extent to which consumers are compelled to draw on either external stimulus or internal memory in selecting from an assortment of online channels. Under this frame of reference, e-mail campaigns and bargain-driven meta-coupon sites (e.g., DealsPlus) can be regarded as stimulus-driven channels, whereas portals and direct apps can be characterized as memory-driven pathways.

Rottenstreich et al. (2007) linked the memory-stimulus archetype with the cognitive mental processing framework instituted by Kahneman and Frederick (2002). Whereas memory-based operation reflects "System 1" processing characterized as automatic, rapid, associative, and inductive, the stimulus-based cognitive mode mirrors the "System 2" mechanism regarded as controlled, deliberate, and deductive (Rottenstreich et al. 2007). Given that System 1 is typified by rapid operation, Kahneman and Frederick (2002) posit that with such processing, judgmental questions are intuitively addressed; that is, individuals respond to the questions as they arise. By contrast, System 2 is not spontaneously activated; an individual therefore engages in a more deliberative consideration of available options before settling on a choice. If we are to subscribe to these viewpoints, then intuition is an operating norm that falls within the rubric of Systems 1, whereas reasoning is a working principle belonging to System 2 (Kahneman 2003). Furthermore, the rapid and automatic System 1 processing is usually less affected by distractions, whereas the slow and self-controlled System 2 mechanism is vulnerable to cognitive interruptions (Shiffrin and Schneider 1977).

In the context of social commerce, consumers who land at SCSs through memory-based channels (e.g., mobile apps and portal sites) are more likely to purchase than consumers who are shepherded to SCSs via stimulus-based channels (meta-coupon sites and email campaigns). Consumers who employ memory-

[3] In this study, we focused exclusively on price-based stimuli since consumers who visit daily deal social commerce platforms are assumed to be price-sensitive.

based channels voluntarily arrive at SCSs with purchase intent. When making purchase-related decisions, these consumers rely on System 1 procedures by which they make rapid and inductive purchase decisions. They are also largely resistant to cognitive load (e.g., competing products) that may diminish purchase intent. Conversely, consumers who are lured to SCSs via stimulus-based elements interpret low prices and deep discounts as cues for careful deliberation and naturally prolong decision-making when encountering incongruence (e.g., substantial differences between regular and discounted prices) (Wathieu and Bertini 2007). Incongruent price differentials induce deliberation and decelerate decision-making (Meyers-Levy et al. 1994; Ozanne et al. 1992; Stayman et al. 1992) as evident in System 2 procedures. Disparate information that emanates from heavy discounts off the reference prices may prompt arousal and cognitive elaboration among SCS consumers who seek to make sense of the source of such incongruences. This elaboration, along with the high vulnerability to cognitive load, may cancel or delay purchase intent (Walsh and Yamin 2005) and consequently diminish the willingness to purchase. These arguments lead us to formulate the following hypothesis:

H1: Consumers who use memory-based channels exhibit higher purchase propensities than do consumers who adopt stimulus-based channels.

Moderating Effects of Product Characteristics on Purchase Propensities

Consumer behaviors may substantially vary depending on the types of products that they purchase. On the basis of consumers' ability to locate product quality information prior to purchase, Nelson (1970) identified two broad categories of products, namely, search and experience goods. This product taxonomy has been widely adopted by researchers in an effort to understand the idiosyncrasies inherent in consumers' purchase behaviors that are driven by the unique characteristics of each product type. Search goods (e.g., USB disks, clothing, binders) typically refer to commodities for which the attributes most critical to the evaluation of product quality can be assessed before purchase. Contrastingly, experience goods (e.g., food, books, and travel packages) are commodities with attributes that are recognizable only after product usage. In this respect, experience goods are characterized by higher quality uncertainty and information asymmetry than search goods (Animesh et al. 2010; Pavlou et al. 2006). The information asymmetry and quality uncertainty that surround products and services have been noted as major sources of the market frictions that confront social commerce. Opportunistic sellers exploit the adverse selection that is caused by information asymmetry. Many SCS patrons are often displeased with inaccurate product descriptions, service failures, and low quality products. A noteworthy issue is that many of the products available through social commerce venues have experience attributes in that their quality is difficult to evaluate prior to purchase. In addition, consumers must use their own sensory faculties to determine the quality of experience goods (Mudambi and Schuff 2010). Therefore, the presence of product uncertainty and information asymmetry is higher in experience goods than in search goods.

Research has shown that product uncertainty can influence consumers' search patterns and purchase behaviors. For example, Pavlou et al. (2006) avers that the uncertainty arising from information asymmetry and adverse selection significantly influences consumers' purchase decisions. Similarly, Luo et al. (2012) demonstrated that high product uncertainty substantially lowers consumer confidence and satisfaction. Because product uncertainty has impeded the full potential of social commerce, an important requirement is to take the uncertainty factor into account when evaluating consumers' buying propensities. We can argue that consumers who access memory-based channels make quick, intuition-based decisions while engaging in product searches, thereby exhibiting higher conversion rates for search goods than for experience goods. The former does not require extensive quality evaluations, whereas the latter necessitates reasoning and cognitive deliberation to determine quality. By contrast, stimulus-based channels are compatible with experience goods because these pathways systematically encourage conscientious decision-making and rational cognitive reasoning before arrival at choices. Purchasing experience goods requires deliberative thinking and rationalization, seeing as their quality attributes are more uncertain and difficult to evaluate. Using these arguments as bases, we develop our hypotheses as follows:

H2A: Consumers using memory-based channels evince higher purchase propensities for search goods than experience goods.

H2B: Consumers using stimulus-based channels manifest higher purchase propensities for experience goods than search goods.

Effects of Internal Channels on Direct and External Channels

Consumers arrive at SCSs through either direct channels (e.g., apps) or external mediating channels. However, internal channels, such as the recommendation systems available within websites, may influence customer conversion upon arrival at a site (Johnson et al. 2003; Li and Kannan 2014; Zauberman 2003). For example, recommendation systems can potentially enhance customer loyalty, increase sales, drive higher advertising revenues, and generate benefits from targeted promotions (Ansari et al. 2000). An issue that remains unclear, nonetheless, is how landed consumers, regardless of their "origins," behave when confronted with recommendation systems, which propose alternative products on the basis of purchase records, product ratings, and user profiles (Fleder and Hosanagar 2009). Moreover, little is known about whether consumers who directly enter SCSs are more likely to make a purchase through recommendation systems than are consumers who are escorted to SCSs through external mediating channels. Finally, no attention has been paid to the extent to which purchasing propensities vary across memory- and stimulus-based channels before and after a firm's adoption of recommendation systems.

We postulate that the effects of recommendation systems on sales may vary depending on the channels through which consumers arrive at SCSs. The extant literature is replete with positions that highlight the positive effects of recommendation systems on sales. For example, De et al. (2010) revealed that recommendation systems significantly enhance firm sales given that consumers purchase both frequently promoted products and non-promoted products through such mechanisms. Similarly, Pathak et al. (2010) found that recommendation systems not only improve retail sales but also offer sellers the flexibility to adjust prices. Häubl and Trifts (2000) demonstrated that such decision tools motivate consumers to reduce search efforts and increase the quality of consideration sets.

In contrast to previous studies, we argue that recommendation systems often result in adverse, unwanted impacts on sales at individual levels. These systems or internal channels typically offer additional options. Studies (e.g., Huffman and Kahn 1998; Scheibehenne et al. 2009) have demonstrated that expanded consideration sets may overwhelm consumers' cognitive capabilities, increase confusion, and discourage purchase intent. Iyengar and Lepper (2000) indicate that consumers exposed to an assortment of choices are not only demotivated from completing their purchases but are also dissatisfied with their choice decisions. In short, in certain environments choices can be more of a curse than a blessing, and when it comes to sales, such curse can originate from recommendation systems. Overall sales volume may increase at the aggregate level after the introduction of recommendation systems because individuals buy additional items for which purchase is originally unplanned. In other words, vendors can benefit from induced or latent demand (Smith 1976). The potential downside, however, is that the presence of recommendation systems that proffer many options diverts consumers' attention and increases their cognitive thought-processing, thereby discouraging them from making purchases. From the perspective of the memory-stimulus framework, recommendation systems can be viewed as stimuli that influence consumer choices, cognitive operations, and, subsequently, purchase willingness. When encountering recommendation systems, consumers who use memory-based channels in entering SCSs now undergo stimulus-based procedures, which increase their cognitive load and encourage deliberate and controlled decision-making. For example, consumers who make their way to SCSs via portal sites come across stimulus elements that encourage them to compare the different options available through recommendation systems and identify the source of incongruence among them (e.g., differences in product and price). Consequently, the stimulus-based procedure driven by recommendation systems may diminish the likelihood that consumers will purchase. By contrast, consumers who are ushered to SCSs via stimulus-based channels (e.g., e-mails and metasites) are affected to a lesser extent by the presence of recommendation systems because they have already experienced such cognitive procedures prior to their arrival at SCSs. In line with these ideas, we propose the following hypothesis:

> *H3: The adverse effect of recommendation systems on sales is more pronounced for consumers arriving at SCSs through memory-based channels than for consumers entering via stimulus-based channels.*

Data Description and Empirical Validation

Data

We validate the proposed hypotheses using mobile click-stream data collected from a major SCS in Korea. The data set includes detailed information about the browsing and purchasing behaviors of consumers who were ushered to the SCS through a variety of external mediating channels (e.g., meta-coupon sites, portals, and e-mails) and through direct channels (e.g., mobile app) during a three-month period (May 1 to July 31, 2013). The consumer-level panel data also contain comprehensive information on deals and products, such as offered prices, discount rates, product categories, and duration of offers. We focused on the top six most popular product categories (fashion items, food, home supplies, restaurants, travels, and service products) to exhaustively analyze how intermediary channels influence purchasing propensities. These six categories represent 71.49% of the products sold at the SCS. The rest are niche products that are difficult to categorize. The samples include only the consumers who purchased at least one product during the three-month period. The final sample comprises 15,439 consumers, 19,004 deals, and 385,198 click observations (Table 1).

Table1: Frequency distributions for the channel-category combinations (parentheses indicate the ratio of the respective segment)

	Category						
	Fashion	Food	Home Supply	Restaurant	Travel	Service	Total
Mobile app	34,079	12,709	11,602	15,795	23,846	8,598	106,629
	(0.088)	(0.033)	(0.030)	(0.041)	(0.062)	(0.022)	(0.277)
Metasites	73,382	27,566	22,425	55,461	44,294	21,343	244,471
	(0.191)	(0.072)	(0.058)	(0.144)	(0.115)	(0.055)	(0.635)
Portal	3,604	819	781	990	1,901	395	8,490
	(0.009)	(0.002)	(0.002)	(0.003)	(0.005)	(0.001)	(0.022)
E-mail	14,565	3,002	2,857	1,601	3,013	570	25,608
	(0.038)	(0.008)	(0.007)	(0.004)	(0.008)	(0.001)	(0.066)
Total	125,630	44,096	37,665	73,847	73,054	30,906	385,198
	(0.326)	(0.114)	(0.098)	(0.192)	(0.190)	(0.080)	(1.000)

We classify each consumer's click observations on the basis of the deal categories and channels through which he or she arrived at the SCS site. We also observe consumers' behavioral patterns specific to deals; an example is the number of repeat visits (*deal visit*) for a given deal or the time elapsed since the deal's launch (*click time*). Our data also include deal-specific information, such as original price (i.e., price before discount) and discount rates. See Table 2 for summary statistics for these parameters. Finally, the purchase scenario-related indicators, such as product categories and channel usage, are included in the data.

Table 2. Summary statistics

Variable	Mean	Std.Dev	Min	Max
Deal Visit	2.4135	4.1867	1	176
Click Time	9.9966	11.5034	0	282
Original Price	75620.7	148526	1	4195400

(Korean won)				
Discount Rate (%)	43.0602	23.2210	0	99
External Channel				
Mobile App	0.2768	0.4474	0	1
Metasites (base)	0.6347	0.4815	0	1
Portal	0.0220	0.1468	0	1
E-mail	0.0665	0.2491	0	1

Notes: 1USD = 1124.57 Korean Won on average during the observation periods.

Model Development

We examine the heterogeneity in customers' purchase intentions on the basis of a mixed logit model framework utilizing hierarchical Bayes procedures. We assume that an individual's decision on whether to purchase a deal can be explained by the random utility model. Consumer i makes a purchase decision at time *t* when the utility derived from purchase exceeds a certain threshold.

$$d_{it} = 1 \ \ if \ u_{it} > 0$$
$$= 0 \ \ if \ u_{it} \leq 0$$

Utility is assumed to be influenced by consumers' usage of an external channel, unobservable deal-specific characteristics, and other related consumer behaviors. Hence, we define customer *i*'s (i =1,2,…,N) indirect utility function for his or her purchase decision on occasion *t* (t =1,2,…T) as follows:

$$u_{it} = a_i^* + \sum_{c=2}^{C} a_{ic}\, I_{ict} + X_{1it}\beta_{1i} + X_{2it}\beta_{2i} + \varepsilon_{it}$$

The unobserved component of utility (ε_{it}) is assumed to follow a Type 1 extreme value distribution. Table 3 shows the description of related variables and parametric elements.

Table 3. Description of Variables and Parametric Elements

	Description	Parametric Elements
I_{ict}	External mediating channel c adopted by consumer i at time t	·Mobile App ·Portal ·E-mail
X_{1it}	Consumer-specific, deal characteristics on occasion t	·Deal Visit : Previous purchase opportunities ·Click Time : Time elapsed since launch
X_{2it}	Deal-specific characteristics	· Original price(scale : 1/10000), · Discount rates (scale : 1/100)

The hierarchical Bayesian framework is useful to make inferences on the individual-specific unobserved heterogeneity. Specifically, our model captures the intrinsic preference of consumer *i* for purchase (i.e. via the base channel which is meta site) (a_i^*); his or her time-invariant deviation in intrinsic preference for purchase via the channel c (α_{ic}), and the consumer-specific response parameters associated with X_{1it} and X_{2it} (β_{1i}, β_{2i}). Let $\theta_i = \{\beta_{1i}, \beta_{2i}, a_i^*, a_{ic}\}$ denote a consumer-specific coefficient:

$$\theta_i \sim MVN(\theta, \Sigma)$$

Using the observed choices for consumer i, $\mathrm{d_i} = \{\mathrm{d_{i1}}, \cdots, \mathrm{d_{iT_i}}\}$, we can construct his or her conditional likelihood as

$$L\{d_i|\theta_i) = \prod_{t=1}^{T_i}[\frac{exp(a_i^* + \sum_c^C a_{ic}\, I_{ict} + X_{1it}\beta_{1i} + X_{2it}\beta_{2i})}{1 + exp(a_i^* + \sum_c^C a_{ic}\, I_{ict} + X_{1it}\beta_{1i} + X_{2it}\beta_{2i})}]$$

The prior on mean θ is assumed to follow a diffuse normal distribution (i.e. with an extremely large variance) and the prior on variance $\sum$ is the diffuse inverted Wishart. When it comes to estimation, we use Gibbs sampling (e.g., Casella and George 1992; Geman and Geman 1984) for $\theta, \sum$ and θ_i at $i = 1, \cdots, N$ where the posterior is:

$$\theta, \sum and\ \theta_i\ for\ i = 1, \cdots, N \ \propto \prod_{i=1}^{N} L(d_i\,|\theta_i) \cdot \varphi(\theta_i|\theta, \sum) \cdot prior(\theta, \sum)$$

Considering each consumer-specific θ_i as a parameter, we construct the layers of the Gibbs sampling for the three sets of parameters as follows:

$$\theta|\sum, \theta_i \qquad \forall\ i = 1, \cdots, N$$

$$\sum|\theta, \theta_i \qquad \forall\ i = 1, \cdots, N$$

$$\theta_i|\ \theta, \sum$$

where the last layer for each consumer-specific parameter $\theta_i|\ \theta, \sum$ uses the Metropolis-Hastings algorithm (e.g., Chib and Greenberg 1996; Hastings 1970). Utilizing such Bayesian procedures to estimate consumer-specific parameters, we are able to avoid the computational failures of classical methods in locating maximum likelihood (Train 2003). Although we allow for the normal distribution of the consumer-specific response parameters, we specify the log-normal distribution of the coefficient for a price discount rate because we expect the same sign for all consumers.

Results

Main Results

Tables 4 presents the estimation results derived from the MCMC procedures. The estimates represent the posterior means and variances. We run the MCMC chain for 40,000 iterations with the first 30,000 iterations discarded to account for burn-in and every tenth draw retained after the convergence. Convergence is assessed by monitoring the time series of the draws. Parameters involving the metasite channel are used as bases for comparison. Using the meta-coupon channel as a default is reasonable because it comprises the largest share of observations. The variable "*deal visit*" refers to the tally of repeat clicks that a consumer makes on a specific deal. The data show that the number of deal visits is positively associated with purchase propensity, suggesting that consumers who repeatedly click on a particular deal are more likely to purchase the advertised product. "*Click time*" represents the timing of a click made on a particular deal. Some SCS consumers click on a deal as soon as it becomes available, whereas others do right before its expiration. The results reveal that click time is negatively related to purchase propensity, implying that the earlier a consumer clicks on a deal after it becomes available, the more likely that he or she will purchase the product included in the deal. Finally, although price is negatively associated with purchase likelihood, discount rate exhibits a significant positive relationship. Consistent with expectations, SCS consumers prefer low-priced and highly discounted items.

The results in Table 4 suggest that consumers' purchasing propensities vary significantly across mediating channels. Consumers who enter into the SCS directly through its mobile apps or through portals exhibit higher purchasing propensities than do consumers who land at the SCS by means of email campaigns and metasites. Surprisingly, consumers who land through metasites present the lowest purchase likelihood among the consumers who arrive at the SCS through the four channels. The findings collectively indicate that memory-based channels (mobile apps and portals) outperform stimulus-based channels (e-mails and metasites) in terms of purchasing propensities. This result lends empirical support to Hypothesis 1.

Table 4. Variations of purchasing propensities across channels

	Mean		Variance	
Base Constant	-4.2472	(0.0166)	0.0580	(0.0128)
Deal Visit	0.4197	(0.0086)	0.1014	(0.0050)
Click Time (daily)	-0.0458	(0.0015)	0.0026	(0.0001)
Original Price	-0.0261	(0.0015)	0.0028	(0.0002)
Discount Rate	0.8125	(0.0361)	1.1615	(0.0341)
External Channel (base : Metasites)				
Mobile App	2.5393	(0.0341)	5.1761	(0.1661)
Portal	1.3569	(0.0665)	0.4598	(0.0944)
E-mail	0.4936	(0.0331)	0.1260	(0.0181)

Notes. Posterior means and posterior deviations (in parentheses) are reported, and all estimates are significant at 95%

Moderating Effects of Product Uncertainty

To verify Hypothesis 2, we choose two products categories (fashion items and travel goods), which have been extensively used to represent search and experience goods, respectively. Determining product types precisely in accordance with search and experience classifications (Nelson 1970) poses a burdensome challenge because many products are subjectively assessed (Animesh et al. 2010). In addition, the advent of electronic and mobile markets and the prevalence of online reviews have changed the nature of products beyond the simple search-experience categorization. To address this issue, we focus on clothing and travel categories, which are considered high in search and experience qualities, respectively (Zeithaml 1981). To minimize structural bias that may arise from consumers' skewed preferences, we restrict the samples to include only the 4,543 consumers who clicked on two categories at least once. This rigorous sampling procedure is necessary because we estimate individual utility indirectly from the purchases of different product categories on the basis of Bayesian inference. We classify the observations of each consumer's 131,026 clicks with reference to the deal categories and channels through which he or she arrived at the SCS site (Table 5).

Table5: Frequency distributions for the category-channel combinations (fashion items and travel goods only)

		Channel				
		Mobile app	Metasites	Portal	E-mail	Total
Product Category	Fashion (search goods)	20,576	48,313	1,439	9,349	79,677
		(0.157)	(0.369)	(0.011)	(0.071)	(0.608)
	Travel (experience goods)	14,884	32,753	1,093	2,619	51,349
		(0.114)	(0.250)	(0.008)	(0.020)	(0.392)
Total		35,460	81,066	2,532	11,968	131,026
		(0.271)	(0.619)	(0.019)	(0.091)	(1.000)

Utility is assumed to be influenced by consumers' purchase scenarios (category-channel), unobservable deal-specific characteristics, and other related consumer behaviors. We hence define customer *i*'s (i =1,2,…,N) indirect utility function for his or her purchase decision on occasion t (t =1,2,…T) as follows:

$$u_{it} = a_i^* + \sum_{f=2}^{F} a_{if}\, I_{ift} + X_{1it}\beta_{1i} + X_{2it}\beta_{2i} + \varepsilon_{it}$$

I_{ift} takes a value of 1 if the f purchase scenario(category-channel) is associated with consumer's purchase occasion t. Metasites and fashion items are used as bases given that this combination accounts for the largest share of observations. Table 6 provides the estimation results, which indicate that the statistical validation for the key attributes (deal visit and click time) remains unchanged even when focus is exclusively directed toward these two product categories. The bottom section of Table 6 presents the estimation derived from the Bayesian MCMC procedures. The values under the category & channel sections of Table 6 indicate the posterior distributions of individuals' specific purchase preferences across all category-channel scenarios. All estimates are significant at the 95% confidence interval; the figures denote the statistical significance of a given scenario relative to the base scenario (i.e., the Fashion Item-Meta App scenario). For example, the Portal-Travel scenario statistically differs from the Fashion Item-Meta App scenario in terms of induced purchase propensities.

Table 6 . Conversion differences between search goods and experience goods

	Mean		Variance	
Base Constant	-4.9821	(0.0278)	0.0445	(0.0039)
Deal Visit	0.4535	(0.0147)	0.1207	(0.0105)
Click Time	-0.0731	(0.0034)	0.0061	(0.0004)
Original Price	-0.0678	(0.0048)	0.0045	(0.0004)
Discount Rate	0.8773	(0.0332)	1.0990	(0.0166)

		Product Category			
		Fashion (search)		Travel (experience)	
		Mean	Variance	Mean	Variance
External Channel	Mobile App	0.6568 (0.0793)	2.0341 (0.2745)	0.2743 (0.0505)	0.7863 (0.0769)
	Metasites	(base)		0.9354 (0.0328)	0.2514 (0.0509)
	Portal	0.8508 (0.1120)	1.7629 (0.2969)	1.0721 (0.0839)	0.5856 (0.0614)
	E-mail	0.5461 (0.0857)	0.3577 (0.0479)	1.0424 (0.0747)	0.4843 (0.1015)

Notes. Posterior means and posterior deviations (in parentheses) are reported, and all estimates are significant at 95%

To validate Hypothesis 2, we aggregate the diverse channels into two groups (memory-based and stimulus-based categories) and carry out the statistical procedures similar to those shown in Table 6. The stimulus-based channel and fashion item pair is used as basis because this combination accounts for the largest share of observations. We find mixed support for Hypothesis 2. The findings suggest that consumers who land at the SCS through stimulus-based channels exhibit higher purchase propensities for experience goods (travel goods) than for search goods (fashion items) (see Table 7). This result is consistent with H2B. However, consumers who gain entry via memory-based channels also show higher propensities for experience goods than for search goods. In line with this finding, H2A is unsupported by our data.

Table 7. Model Estimation Results (Interaction between channel type and product characteristics)

	Mean		Variance	
Base Constant	-4.9369	(0.0996)	0.0674	(0.0124)
Deal Visit	0.4575	(0.0209)	0.1266	(0.0129)
Click Time	-0.0811	(0.0050)	0.0066	(0.0006)
Original Price	-0.0674	(0.0032)	0.0045	(0.0003)
Discount Rate	0.9277	(0.1095)	1.1614	(0.0572)

		External Channel			
		Memory		Stimulus	
		Mean	Variance	Mean	Variance
Product Category	Fashion	0.6328 (0.0844)	1.8214 (0.3626)	base	
	Travel	1.6963 (0.0879)	2.3941 (0.4049)	0.9332 (0.0631)	0.2354 (0.1171)

Notes. Posterior means and posterior deviations (in parentheses) are reported, and all estimates are significant at 95% .

Field Experiment- Implementation of the New Recommendation System

To investigate the effects of the new recommendation system on consumers' purchase propensities, we divide the three-month into two sub-periods; one before and one after the adoption of the new system on June 20, 2013 (Figure 2). The new recommendation system was designed and implemented by the SCS and operated using collaborative and content-based algorithms that incorporate personal preferences into recommendations. To measure the degree of change in the channel preferences of users, we focus our analysis on the 2,195 users who consistently accessed the SCS from the pre-adoption period and who were exposed to recommendation systems at least once after the company's implementation of the system.

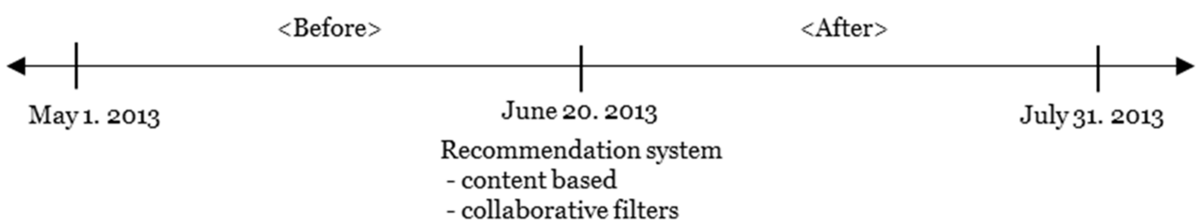

Figure 2: Data setup and analysis design

Table 8 and Figure 3 show the results before and after the SCS's adoption of the new recommendation system that is similar to Amazon's. Users tend to less repeatedly click (deal visit) on a specific deal after the implementation of the recommendation system. The negative relationship between click time and purchase propensities remains unchanged but becomes less pronounced after the implementation of the decision tool. An interesting observation is that the system motivates users to purchase products that are relatively higher in price and lower in discount rate.

Consistent with Hypothesis 3, consumers' purchasing propensities at the individual level decline across all channels after the implementing a recommendation system, although the degree of reduction substantially varies from channel to channel. In particular, mobile apps register the most significant reduction in purchase propensities, whereas the other pathways manifest a slight decline.

Table 8: Purchase propensities before and after the adoption of a recommendation system

	Pre-adoption				Post-adoption			
	Mean		Variance		Mean		Variance	
Base Constant	-4.3431	(0.0410)	0.1122	(0.0382)	-4.6994	(0.0528)	0.0615	(0.0120)
Deal Visit	0.4141	(0.0273)	0.1273	(0.0272)	0.3751	(0.0139)	0.0646	(0.0067)
Click Time	-0.1115	(0.0113)	0.0114	(0.0016)	-0.0587	(0.0039)	0.0053	(0.0004)
Original Price	-0.2108	(0.0209)	0.0228	(0.0042)	-0.0696	(0.0050)	0.0064	(0.0006)
Discount Rate	0.4199	(0.0390)	1.3614	(0.1329)	0.4057	(0.1224)	1.2296	(0.1953)
External Channel (base : Metasites)								
Mobile App	2.1992	(0.1648)	2.4449	(0.5657)	0.4915	(0.0644)	0.6830	(0.1519)
Portal	1.4642	(0.1923)	1.1276	(0.3630)	1.1105	(0.1911)	0.5928	(0.1806)
E-mail	0.3500	(0.0587)	0.1133	(0.0286)	0.3479	(0.0483)	0.1881	(0.0481)

Notes. Posterior means and posterior deviations (in parentheses) are reported, and all estimates are significant at 95%

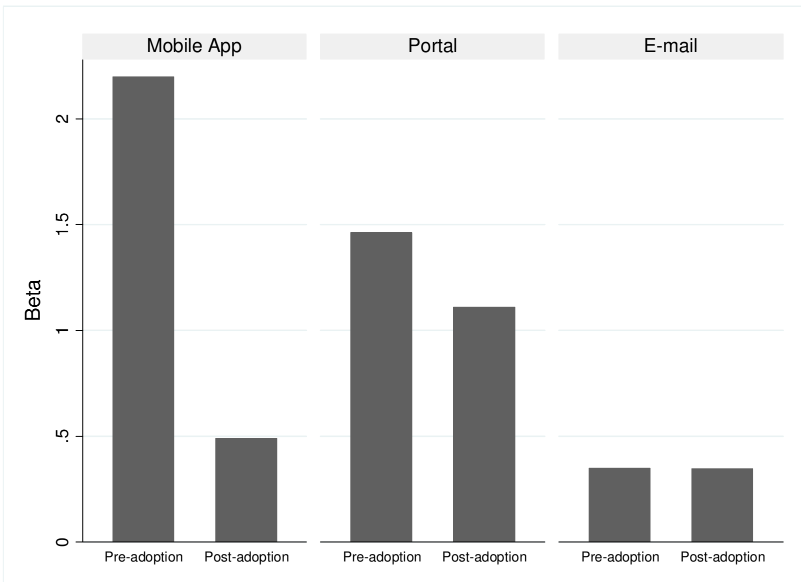

Figure 3. Purchase conversion before and after the adoption of a recommendation system

To validate Hypothesis 3, we aggregate the diverse channels into two groups (memory-based and stimulus-based categories) and carry out the statistical procedures similar to those shown in Table 8. The stimulus-based channel is used as basis because the stimulus channel comprises the larger share of observation. The changes in beta distributions ($\beta_{\text{Post adoption}} - \beta_{\text{Pre adoption}}$) before and after the implementation of the recommendation system suggest that consumers who land at the SCS through stimulus-based channels affected lesser extent than memory-based channels by the presence of recommendation systems. In other words, H3 is supported by the results (Table 9).

Table 9: Purchase propensities before and after the adoption of a recommendation system

	Pre-adoption				Post-adoption			
	Mean		Variance		Mean		Variance	
Base Constant	-4.2249	(0.1113)	0.1676	(0.4094)	-4.6026	(0.0849)	0.0682	(0.0072)
Deal Visit	0.4257	(0.0351)	0.1490	(0.3860)	0.3781	(0.0170)	0.0055	(0.0004)
Click Time	-0.1178	(0.0099)	0.0122	(0.1103)	-0.0597	(0.0042)	0.0065	(0.0006)
Original Price	-0.2249	(0.0239)	0.0260	(0.1613)	-0.0699	(0.0052)	0.2144	(0.1328)
Discount Rate	0.2557	(0.0946)	1.5330	(1.2381)	0.2119	(0.0588)	0.0799	(0.0185)
External Channel (base : Stimulus Channel)								
Memory Channel	2.0124	(0.1389)	3.0153	(1.7365)	0.5443	(0.0688)	0.6470	(0.1482)

Notes. Posterior means and posterior deviations (in parentheses) are reported, and all estimates are significant at 95%

Figure 4 shows the changes in beta distributions before and after the implementation of the recommendation system. Whereas e-mail channels are almost unaffected by the recommendation system, other channels experience left shifts in beta distribution, indicating a sizable decline in purchase propensities after the institution of the system. Intriguingly, although purchase propensities diminish, the average spending per purchase increases after the implementation of the recommendation system (*p*<0.01) (Figure 5).

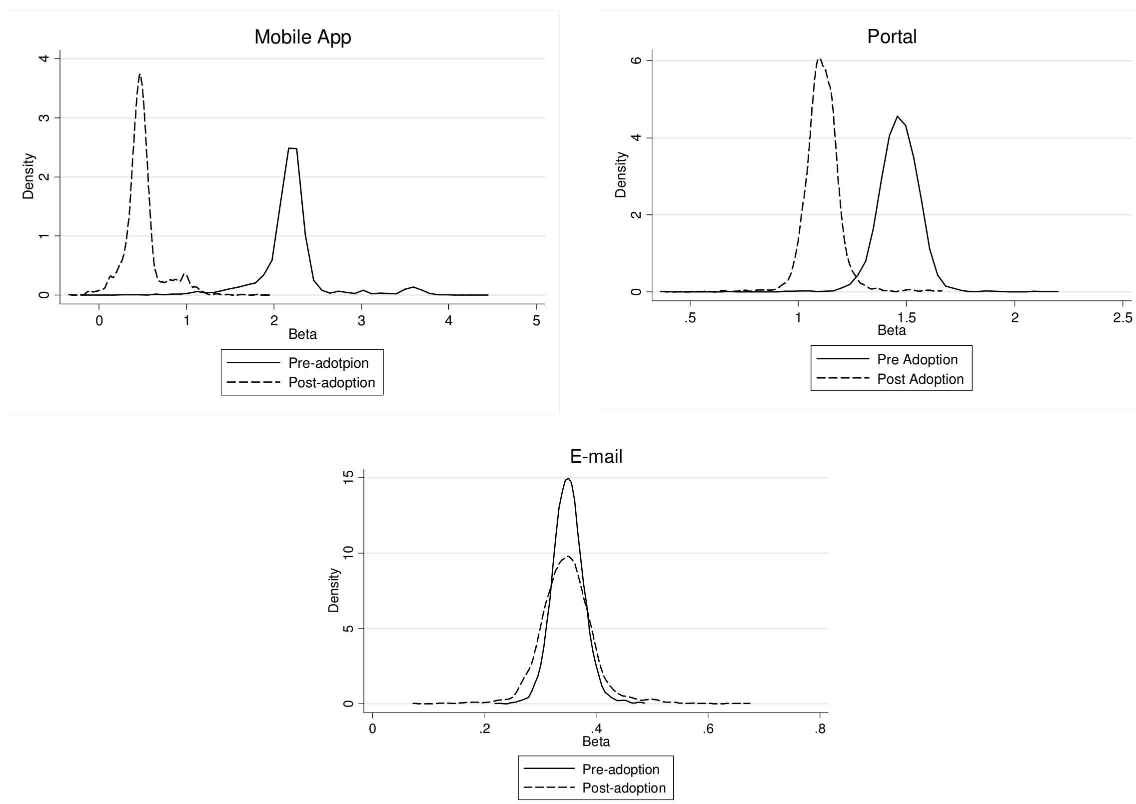

Figure 4: Shifts in beta distributions before and after the implementation of a recommendation system

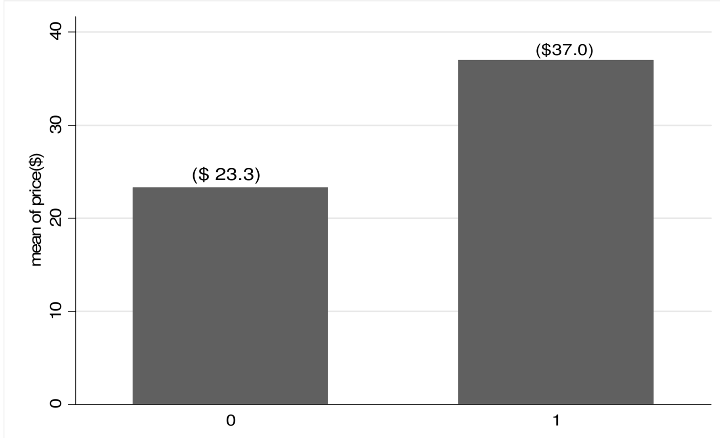

Figure 5: Average spending per purchase before and after the adoption of a recommendation system

Implications

This study has several implications for research and practice. We underpin the work with the memory-stimulus framework to conceptually categorize and evaluate a variety of online mediating channels through which consumers land at social commerce platforms and purchase products with varying degrees of uncertainty. On the basis of 385,198 observations collected from 15,439 SCS consumers, we empirically assess the economic value of direct and indirect mediating channels for social commerce. To the best of our knowledge, this study is among the first to disentangle the dynamic role of "digital intermediaries" in sales conversion under the context of social commerce. Our theoretical extensions may shed light on the etiology of purchase conversion in social commerce, wherein market friction poses important implications for revenue growth and longevity.

We also delve into the dynamic interplay between external intermediaries and internal channels (e.g., recommendation systems), which has been accorded minimal scholarly attention. Most previous studies predominantly assert that recommendation systems increase revenues. The current research deviates from this tendency articulating the situations in which such infrastructures negatively, rather than positively, influence sales, at least at the individual consumer level. Our findings indeed run contrary to conventional wisdom and to the thrust of conventional scholarship, revealing that purchase conversion markedly diminish for consumers who use direct channels (i.e., users that enter into SCSs by activating a retailer's mobile apps) after being exposed to active recommendation systems. Other channels (e.g., portals and metasites) pose similar adverse consequences, albeit not as severely as those presented by mobile apps. Given this backdrop, researchers should espouse a more balanced view when evaluating the economic value of recommendation systems. These decision aids can both facilitate and impede sales, as well as motivate consumers to purchase additional product quantities for which purchase is originally unplanned; this motivated behaviors triggers "induced demand"(Smith 1976). Such systems may also encourage consumers to delay or cancel purchase as they are confronted with more options from which to choose. Choices often demotivate purchase intent and increase dissatisfaction with selected products (Iyengar and Lepper 2000)). Our findings provide empirical evidence for such adverse effects of recommendation systems.

Retailers can also benefit from the empirical regularities observed in this study. Memory-driven channels, such as direct apps and portals, effectively drive sales in social commerce. In particular, mobile apps stimulate exceedingly higher purchase propensities than do stimulus-driven channels, which typically motivate purchase from consumers with discount incentives. By contrast, consumers who are ushered to SCSs through stimulus-induced channels, such as e-mail promotions and meta coupon sites, exhibit substantially lower purchase propensities. This finding suggests that consumers harbor a natural tendency to downplay price incentives, particularly when advertised discounts are set excessively high. Many SCSs exploit stimulus-channels, including coupon sites and e-mail promotions with heavy discounts in an attempt to attract consumers to their sites, but such price-driven campaigns will not pay sufficient dividends to retailers. SCS vendors should understand that competing solely through price promotions is a risky proposition in social commerce. Instead, they should more aggressively pursue initiatives grounded on memory-driven channels, especially mobile apps, because these pathways stimulate increased focus on purchase trajectories and encourage consumers to take rein over their search routines.

Compared with stimulus channels, mobile apps enable exceptionally high conversion propensities for search goods (fashion items). Nevertheless, their capability to elicit sales for experience goods (travel goods) substantially diminishes. This result contrasts with the findings derived for other channels in which purchase likelihood for experience goods is relatively higher than that for search goods. This is an intriguing result given that travel goods are usually far more expensive than fashion items. However, interestingly, many SCS sellers currently use meta coupon sites to sell mostly search goods, such as clothing, home supplies, and electronics. These sellers should carefully reassess their channel strategies contingent on product characteristics.

Today, recommendation systems have become a business necessity in online retailing sectors. An issue taken for granted by vendors is that such decision aids reduce consumers' search costs and generate additional revenues. Although these benefits may be derived, in certain environments recommendation systems can also diminish consumers' purchase propensities because they are confused by the availability of numerous options. Choice may be a favorable factor, but an excessive selection can hurt. In particular, managers should be alerted to the downside of recommendation systems as they can significantly harm sales, especially those generated from transactions through mobile apps. Our findings suggest that recommendation instruments should provide a moderate quantity of product options, which do not complicate the cognition involved in purchase decisions. Sellers can run experiment on the choice settings of recommendation systems to determine the most ideal configurations.

Conclusion

Social commerce platforms have recently been confronted with an indeterminate future because of plummeting revenues and an inexorable decline in repeat customers. Amid dwindling membership and sales, social commerce stakeholders increasingly attend to consumer–website paths, such as mediating channels through which consumers arrive and make purchases at sites. Scientific understanding of diverse mediating channels as sales agents in e-commerce is rudimentary; this study aspires to fill this void. Using the memory-stimulus perspective as a frame of reference, we examined consumers' purchasing propensities on the basis of the channels through which they are ushered into social commerce venues. The findings suggest that intermediary channels driven by price incentives (e.g., email promotions and coupons) are ineffective in delivering sales despite the common belief that social commerce consumers are highly price conscious and seek heavily discounted items. We also found empirical regularities that may run counter to our intuition regarding the effects of recommendation systems on demand structures and sales generation in social commerce. The analysis reveals that although recommendation systems may increase consumers' average spending per purchase on account of induced demand, they can also motivate potential buyers to delay or cancel intended purchase. The additional options proffered by recommendation systems can even induce consumers with high purchase intent to forgo any of the choices and refrain from making a purchase. The "illusion of choice" orchestrated by the recommendation infrastructure in an attempt to generate additional sales can end up motivating people to leave a site without following through with a purchase. Moreover, such adverse effects substantially vary across consumers depending on the channels through which they arrive at social commerce platforms. Given that consumers' purchase journey becomes more complicated and fragmented in online environments, marketers are strongly encouraged to look beyond the simple pursuit of conversion and holistically re-assess how their channel strategies fit within the customer journey.

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