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HOW DO CONSUMERS USE SOCIAL SHOPPING WEBSITES? THE IMPACT OF SOCIAL ENDORSEMENTS

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HOW DO CONSUMERS USE SOCIAL SHOPPING WEBSITES?

THE IMPACT OF SOCIAL ENDORSEMENTS

DISSERTATION

A dissertation submitted in partial fulfillment of the
requirements for the degree of Doctor of Philosophy in the
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By

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ABSTRACT OF DISSERTATION

HOW DO CONSUMERS USE SOCIAL SHOPPING WEBSITES?

THE IMPACT OF SOCIAL ENDORSEMENTS

Social endorsements are user-generated endorsements of products or services, such as “likes” and personal collections, in an online social platform. We examine the effect of prior social endorsements on subsequent users’ tendency to endorse or examine a product in a social shopping context, where a social platform connect consumers and enable a collaborative shopping experience. This research consists of two parts. In part I, we identify two ways prior social endorsements can affect subsequent user behavior: as a *crowd endorsement*, which is an aggregate number of endorsements a product receives for anyone who comes across the product, and as a *friend endorsement*, which is an endorsement with the endorser’s identity delivered only to the endorser’s friends or followers. Using a panel data of 1656 products on a leading social shopping platform, we quantify the relationship between crowd and friend endorsements and subsequent examination (“click”) and endorsement (“like”) of the products, noting that examination is a private behavior while endorsement is a public behavior. Our results are consistent with the identity signaling theory where identity-conscious consumers converge with the aspiration group (the followers) in their public behavior (e.g. endorsement) and diverge from the avoidance groups (the crowd). We also find differences between public and private behaviors. Moreover, the symbolic nature of social shopping platform trumps the traditional dichotomy of symbolic/functional product attributes. Part II of this study seeks to clarify the underlying mechanism through lab experiments. We hypothesize that consumers' evaluative attitude, specifically the value-expressive type, moderates the relationship between crowd and friend endorsements and a focal user's product choice. Our initial results of the second study show support for this idea in the cases when the product choice is not obvious.

KEYWORDS: Social Shopping, Social Endorsement, User-generated Content, Social Influence, Recommendation System

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THE IMPACT OF SOCIAL ENDORSEMENTS

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To Abby

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Chapter 1. Introduction

Social shopping sites, which emerged in 2005, are considered the next big thing on the Internet (Guynn 2006; Jones 2013; Wang et al. 2012). Social shopping is a form of electronic commerce that uses social media technologies to connect consumers and to enable a collaborative product exploration and shopping experience. On social shopping platforms, consumers are no longer mere recipient of product information and recommendations, they also actively engage in content curation (e.g. user-generated product lists, collections, tags, and favorites), content creation (e.g., ratings, reviews, and idea boards), content sharing with shopping-focused communities and forums. Rather than being a brand new phenomenon, social shopping is viewed as the convergence of social networking, user-generated content, and e-commerce (Curty et al. 2011). Applications of social shopping can be found in areas of fashion (e.g. Polyvore and Stylehive), interior design (e.g., Polyvore), furniture (e.g., ShopStyle), baby gear (e.g., Wishpot), and so on (Leitner et al. 2008; Leitner et al. 2009; Stampino 2007; Wang et al. 2012). Ebay estimates that the value of social shopping will reach $5 billion by 2014 (Brandweiner 2012).

Unlike e-commerce shoppers, social shoppers can not only find products through the familiar computer-generated recommendations (e.g., “similar items”, and “co-purchases”), they can also access a swarm of product endorsements (e.g., likes, lists, and idea boards) generated by socially connected peers. We shall call the latter “*social endorsements*” to differentiate them from traditional computer-generated recommendations and from celebrity endorsements. The term “social”, as in “social media", highlights the fact that these endorsements are generated by peers in an online social platform.

Compared with the e-commerce shoppers, social shoppers tend to be more explorative and hedonically motivated rather than goal-directed and utilitarian-oriented (Goldenberg et al. 2012; Olbrich et al. 2011). By bringing social interaction and influence to shopping processes, social shopping aims to solve the long-standing problem of e-commerce – consumers often have no clear idea of what they want. Hence, social shopping platforms often emphasize the enjoyment of shopping process than outcomes. Indeed, many of the existing social shopping sites are not selling any product themselves but rather connect consumers with products and brands originated elsewhere. This unique value proposition of social shopping presents a rare opportunity to examine the role of consumer endorsements in a more hedonic and experience-oriented shopping contexts.

In this research, we ask the following specific questions: what are the effects of social endorsements on consumers' behaviors? To answer this question, we evaluate the effect of two forms of social endorsements, namely the aggregate number of social endorsements (crowd endorsements) and the atomic social endorsements that travel through friendship networks (friend endorsements), on subsequent consumers' private examination ("click") and public endorsement ("like") of the products. After observing evidence from archival data in the first study, we extend the exploration to consumers' characteristics that influences the effect of disaggregated and aggregated social endorsements.

We contribute to the literature of social media and UGC by examining and highlighting the role of social endorsements in symbolic goods consumption. Symbolic goods are consumed for its symbolic and self-expressive values. The symbolic value of goods evolves over time and exists only within specific social contexts, the demand for symbolic goods is often described as dynamic and “whimsical” (Clement et al. 2006). Moreover, symbolic goods theory suggests that social interaction strongly shape the preference among symbolic goods (Sproles 1981). As such, the roles and effects of social endorsements on symbolic goods consumption can be markedly different from on utilitarian consumption, and deserve separate examinations.

This research is conducted from multiple perspectives and using multiple approaches. First, we use secondary data collected from social shopping websites to study the effects of social endorsements on subsequent consumers’ private examination and public endorsement behaviors at the *product* level. Second, experimental method is chosen to examine how *consumers* utilize crowd and friend endorsements in their product decisions. Because this approach takes the perspective of consumer decision-making, we are able to examine the interplay between individual characteristics and the role of social endorsements. Taken together, the two perspectives provide us a more comprehensive picture. I present the two parts of the dissertation in chapter 2 and chapter 3 as stand-alone studies.

Chapter 2. The Role of Social Endorsement

2.1 Introduction

Online consumer opinions are a vital source of information for many major markets such as online retailing, professional services, and healthcare. The most researched kind of consumer opinions is user-generated reviews (also known as electronic Word-of-mouth) (Chen et al. 2005; Dellarocas et al. 2007; Mudambi et al. 2010). In comparison, namely online product endorsements, such as likes, have received less attention despite their rising popularity (Miller et al. 2013). Unlike online reviews, which require significant effort, online endorsements are often solicited as a part of an overall social system design and can blend well into everyday online user activities. Such endorsements are always positive and can take a variety of different forms, such as likes (Thumb-ups), mentions, deeper involvement with products (e.g. idea boards or user generated innovations), etc. Social advertising — which contains a wide range of ads, including endorsements — is said to be a $9.5 billion business, accounting for 8 percent of digital ad spending (Emarketer 2013).

While there are many similarities between online reviews and online endorsements, several reasons warrant separate attention for online endorsements. First, as mentioned above, online endorsements are more embedded in everyday activities in online social systems and participated by a broader spectrum of users. Therefore, their production may have different patterns from online reviews. Second, because of broad participation and stronger social embeddedness, online endorsements often spread among one's followers or friends, in addition to being presented as an aggregate number (i.e., crowd endorsements). Thus, social endorsements extends word-of-mouth marketing on a broad scale. Finally, because there can be only positive endorsements and for the social fabric underlying social endorsements, consumers' attitudes towards products are likely different from that of online reviews.

Online endorsements enhance audiences' attitudes toward the endorsed product and behavioral intents (Dellarocas 2003; Godes et al. 2009; Godes et al. 2005; Wang 2005). With the exponential growth of social media platforms, endorsers are no longer anonymous users but identifiable consumers connected by online social networks (Daneshvary et al. 2000). In current paper, we define *social endorsements* as product endorsements generated in an online platform with extensive social media features (e.g. user profile, following, etc). Endorsements used to be the privilege of a few high status individuals, typically celebrities or experts (Fireworker et al. 1977). Social media democratize the market for endorsements, such that everyone can freely endorse a product or service and be heard by others.

Online opinions are generally presented in two forms. The first form is an aggregate opinion that is displayed indiscriminately for everyone who comes across the product page. Information presented in this form is aggregate, usually removed of social cues, and indiscriminating – in the sense that all users will see the same information. This is also the primary mode of presentation for digital WOM (e.g. online ratings). The second form is a personalized endorsement messages together with the identity of the endorser, traveling through the endorser's social network (either pushed to or pulled by the recipient). Information presented in this form is usually atomic, rich in social cues, and limited only to socially connected users. Social endorsements typically are presented in both forms: we call social endorsements presented in the aggregate form "*crowd* *endorsements*", for recipients cannot easily tell the identities of endorsers. We call social endorsements presented in the atomic form "*friend endorsements*", for they typically travel from endorsers to their friends. It is worth pointing out that on most social media platforms, the two forms of presentations are blended, that is, social endorsements are presented in both aggregate and atomic forms.

One of the primary challenges in understanding the role of social endorsements in the diffusion of opinions, preferences, and behaviors is how to decouple effects of crowd endorsements and friend endorsements. We can use Facebook "Like" to illustrate this challenge (see Figure 2-1). When "Like" is presented along with a Facebook post, there are two ways such an endorsement can affect a consumer's decision. First, an endorsement by a peer user can affect the subsequent users' decisions in the form of total "likes" that the post has received, which indicates the popularity of the post. In Figure 2-1, 14,408 of the previous viewers have endorsed Samsung's new product. Meanwhile, the recipient receives the endorsement because some of his/her friends have endorsed the product and the identities of some of these friends are highlighted. As shown in Figure 2-1, two friends of the user are among the 14,408 previous endorsers.

Marketing and social network literature has separately documented the impact of each type of signal on subsequent consumers' adoption decisions. The first signal, labelled as "*observational learning*", refers to circumstances where a consumer observes *aggregate* decisions of a population prior to make a selection (often about opinions, preferences or choices) (Aral et al. 2013). The second signal, labelled as "*social influence*", describes how the behaviors of one's social connections change the likelihood that one will engage in that behavior (Aral 2011). Although both signals are separately found to influence consumer actions, without acknowledging the co-existence of both signals, those investigations can be potentially biased. To the best of our knowledge, there are four exceptions have appeared in the literature, which have measured both observational learning and WoM effects (Chen et al. 2011; Cheung et al. 2012; Duan et al. 2009; Li et al. 2013). However, our research differs from these studies in the following key ways: (1) One of the outcomes we evaluated, future endorsements, is publicly observable. A consumer's endorsement behavior on social media platforms is part of his online profile. Other studies investigate consumer decisions that are not known to others, such as purchase. (2) To evaluate the power of WoM, we collect endorsers' social network information, and calculate the scale of recipients, rather than merely collect the number of endorsers. This gives us a more accurate estimation of market exposure of the products.

Figure 2-1 A Facebook post with 14,408 endorsers

Another contribution we attempt to make is to distinguish consumer outcomes related to public and private activities. Many different types of endorsement outcomes have been studied in the domain of social media/UGC, in terms of observational learning and social influence, but to the best of our knowledge, none of the previous studies have distinguished the effect of endorsements on public behaviors from private behaviors. We argue that the public-private dichotomy is a particularly useful and relevant theoretical lens for explaining online consumer behaviors in social systems because consumer identity involvement is frequently activated in such systems when their activities are (perceived to be) public. Social endorsements may affect a slew of activities that consumers may partake related to product discoveries. Online activities such as endorsement, commenting and rating are considered as public behaviors, as they are made known to others. Conversely, activities, such as clicking out products and spending time on investigating products, leave their footprints on web servers, but are not observable to others. Recent research suggests that individuals may act quite differently when they undertake an activity which they think is public rather than private (Ratner et al. 2002; Schlenker et al. 1996). Ratner et al. (2002) suggest that people sometimes make decisions other than those they would privately favor, when they expect others will form impressions of them based on the decisions made. On social shopping websites, chances are that after observing other's product endorsement actions, one would privately favor the product, but not publicly endorse it, in order to avoid indicating unwanted impression formed by others. From the marketer's point of view, the private and public activity also carry different meanings because by definition, public activity may socially influence other consumers' behaviors thus warrant special attention whereas private activities may offer a window into consumers' private costs or benefits. Therefore, it is useful to examine the effect on public versus private activities separately.

A third contribution we attempt to make is a context where products are evaluated not just by their functional value but more by their symbolic value, such as in the cases of fashion products and home décor products. The effect of social endorsements for such products require special attention because symbolic value of such products are often socially constructed (Sproles 1974). In discuss of the prevalent of online consumer opinions, Godes et al. (2005) argue that the increasing importance of eWoM is partly because of the increasing complex of products and product attributes become more "technical", so that average consumer's ability to evaluate these features has diminished and they tend to rely increasingly on each other. This statement tells part of the story. Endorsements on product functional features enhance others' confidence in making adoption decisions (Duan et al. 2009), however, not all adoption behaviors are functional-oriented, while some are merely a way of expressing personal taste. Hedonic products – such as music, movie and designer handbag -- provide more experiential consumption, fun and fantasy (Clement et al. 2006; Hirschman et al. 1982). A user's public endorsement of a hedonic product does not necessary arouse sympathy from others, since most of the time there is no right or wrong, no superior or inferior, in the adoption of those products. In this study, we focus on understanding the effect of public endorsements on hedonic products, in which the evaluation benefit provided is a matter of taste and there is not one best-performing option. Social media accelerated this trend by enticing individuals to publicize their tastes and preferences in exchange for social or other economic benefits (McQuarrie et al. 2013). The hedonic aspect of consumers activities has been overlooked in the recent literature (Aakhus et al. 2012).

We are specifically interested in two subsequent activities after receiving a social endorsement, i.e., the private activity of examining a product (as reflected by clicks) and the public activity of endorsing a product (as reflected by likes). These two outcomes are arguably two most used metrics for the performance of social shopping platforms. There are other important private activities such as clicking out (to a third party) or purchases that are important to social shopping platform, but such data is not available to us and we hope that private examination and public endorsements are theoretically representative and practical relevant enough to warrant investigation. The objective of this paper is to empirically examine the impact of social endorsements on consumer's subsequent public and private behaviors. In this study, we achieve the objective in the following ways.

We examine the effect of social endorsements on subsequent private and public activities of online consumers, while paying special attention to the channels through which these effects occur. We do so in the context of social shopping, which is hailed as the next frontier of online commerce. To put it simply, social shopping websites are a type of electronic commerce platform that uses social media and recommendation technologies to enable collaborative product exploration, curation, evaluation and eventual purchases among connected consumers. Using archival data collected from a leading social commerce website, we find that the more social endorsements a product received the more chances it will be checked out and endorsed. Secondly, observational learning through number of existing endorsements is positively interacted with social endorsements through social influence on future endorsement, but the two mechanisms are negatively interacted on private examination activities. These results suggest that prior endorsements not only reinforce public endorsement, but also substitute the effort putting into private examination activities. Compared with social endorsements, when endorsements are presented through non-social channels, such as via search engine and computer recommendation, consumers seem to differentiate themselves with majority strangers (avoidance group), i.e., products with more endorsements are less likely to be endorsed in the next period.

Social networking features are found to affect user adoption decisions under several online social media contexts such as YouTube (Susarla et al. 2012), Facebook (Goh et al. 2013), Flickr (Zeng et al. 2013), etc. An important contribution we bring to social media and UGC literatures is that we examine and highlight the role of social endorsements for the consumption of symbolic products in a hedonic shopping environment. Even though the context of our study highlights the symbolic aspect of product evaluation, we argue that the insights we obtain can be applied to other online social systems as they often require consumers to reveal their preferences publically in exchange for “social” services, and, in the process, such online social systems heighten the symbolic aspect of product evaluation.

The rest of this paper is organized as follows. We start with discuss the research context and related literature. Next, the theoretical arguments for the main hypotheses are presented. We then describe the data collection process and the research model. Followed this, we presented the results of data analysis, and discuss the implications.

2.2 Research Context and Related Literature

We investigate the effect of social endorsements in the context of social shopping. Social shopping websites provide plenty of features for online shopping: users can add products they find on third party sites. They can create and share “idea boards” or product collections with their friends and followers. Users can vote or comment on ideas created by other users. They may subsequently check out a user’s profile for the user’s most recent “likes”, “idea boards”, or product collections. They may even further follow users so that they will receive a constant “activity stream” of their followings. In additional to these social features, they may also use more traditional e-commerce search and recommendation features: for example, they may navigate amongst products following similar-item, or co-like-based recommendations. All of these features provide an ideal environment for hedonic browsing (Bucklin et al. 2002) – that is, users can spend hours exploring products without necessarily having specific goals. Given multiple sources of information, it is necessary to understand how consumers use them in their product exploration and evaluation processes. In this paper, we are especially interested in the role of endorsements generated by peer users, such as likes and idea boards, which we call “social endorsements.” We ask the following specific questions: what is the role of social endorsements in social shopping environments? Specifically, how do they impact consumers’ product involvement in terms of private examination (e.g. clicks) and public endorsements (e.g. likes)?

Not only do ordinary consumers find themselves get addicted to such websites, businesses are also taking advantage of the power of social endorsements. Companies, such as J Crew, are releasing their new products catalogue through social shopping platforms (Indvik 2013). Companies begin with registering as a user with an official profile, endorse products and keep attracting new followers. After releasing their new products, their followers help promote the products by liking and creating mix-and-match boards. The effect of such marketing is beyond comparison of any other marketing efforts, in terms of the high extent of user involvement. However, with millions of products being endorsed on social shopping platforms every day, how can a product stand out in the competition of attention/effort with other products? More specifically, how can a brand or retail make best use of social shopping websites in marketing their products, given that product quality is already ensured? In this study, we empirically investigate the factors that drive differences in product performance metrics such as clicks, likes and creations.

Research on social shopping is still nascent. The term “social commerce” has been used interchangeable in the literature. Social commerce, according to (Stephen et al. 2009), includes not only connected consumers (social shopping) but also connected sellers. Wang et al. (2012) offer some initial conceptualizations and perspectives about social shopping. Jiang et al. (2012) use survey to study the adoption behavior focusing on the relation between the sender and receiver. Huang et al. (2010) study the perceived usefulness of the item using surveys. Also using survey data, Hsiao et al. (2010) found that trust of social endorsements at social shopping sites is affected by a recommenders’ ability, integrity, and the number of active recommenders.

Olbrich et al. (2011)’s study is the only research on social shopping using archival data. They examined the social shopping features on a leading social shopping website. Interestingly, they found that features like lists and sets function as obstacle in direct shopping (a click-out to the product hosting sites). They argued that lists and styles are not designed for direct shopping, but for enhancing browsing, particularly in the pre-purchase phase. Also, they posited that those novel features distract consumers’ attentions from their originally intended searches. Those findings need to be treated with caution for the following reasons: 1) Their data collection period spanned from May 1, 2009 to Oct 31, 2009, a time when social shopping was not known to majority consumers. 2) The decision of a click out might be counted in a different way, by extending to a longer time frame. Some consumers show a lag in making purchase decisions after discovering the product.

To form an initial understanding of social shopping websites, I start the investigation with analyzing 50 interview scripts from a sample of frequent social shopping website users. Those interviews were published on a social shopping website in the year of 2013 and were conducted by the website (Polyvore 2013). I conducted an analysis of the verbal and visual texts in these interview scripts, with an emphasis on instances in which motivations of social shopping was asserted and displayed. Three themes were found to be very prominent across those interviews. First, self-expressive motivation in social shopping -- users endorse products they like and would love to wear in real life. They consider the endorsement behaviors a way of self-expressing. Second, social interaction is an important factor that influences their shared endorsements. They are aware that other people are also following them, and wish to provide inspiration to their followers. Third, personal styles expressed through product endorsement are dynamic and whimsical. Excerpts of the interviews can be found in Appendix D.

There are two alterative mechanisms that might work in such an online setting: social contagion and herding effect. Social contagion has been investigated in various online social network platforms (Centola 2010; Iyengar et al. 2009; Iyengar et al. 2011; Susarla et al. 2012). Susarla et al. (2012) find that social network positively related with both the initial and later phase of video diffusion on YouTube. Centola (2010) studies the spread of health behavior on artificial forum and find that Individual adoption was much more likely when participants received social reinforcement from multiple neighbors in the social network. Iyengar et al. (2009) posit that the effect of friend influence on the consumption of virtual products varies by user's status. On the other hand herding describes a phenomenon in which individuals converge to a uniform social behavior

(Bikhchandani 1998; Bikhchandani et al. 1992). Informational cascades has been suggested as the primary mechanisms for herding behavior, in which individual follows the adoption decision of the preceding individual without regard to his own information (Bikhchandani et al. 1992). An informational cascade occurs when it is optimal for an online user, having observed others' actions, to follow the adoption decision of the preceding individual without regard to his own information.

2.3 Theoretical Foundations and Hypotheses Development

2.3.1 *The Symbolic Meaning of Online Endorsement*

It is believed that consumer orientation toward product benefits is not only utility based, but is also related with the symbolic value of the products. Two specific symbolic consumption motivations have been proposed: an instrumental orientation and a self-expressive/hedonic orientation (Solomon et al. 1987). First, products with strong symbolic connotations may be consumed primarily because they are perceived as instrumental in achieving desired social goals. Membership in the "right" club may be perceived as necessary to achieve acceptance within a desired social group. Add some examples. Second, a product decision may also be motivated by self-expressive or hedonic reason (Hirschman et al. 1982). For instance, a person may choose wine based on personal preferences rather than on popular opinions. Similarly, the choice of furniture styles for the home may be primarily directed toward expressing the buyer's aesthetic taste rather than to connote social status. Both of the two motivations help construct a person's identity.

As online activities become an increasingly important portion of human lives, there are a natural desire for human beings to build their identities and coordinate their relationships in online worlds (Aakhus et al. 2012). One of the most important features of social media websites, as discussed by Kane et al. (2014), is that the platform provides a profile for each user that is collectively contributed by the user, by members of the user's online social network, and by the platform. Online endorsements as part of users' online profiles reflect their product tastes and are perceived to denote the users' social identities. Through online display of product endorsements, consumers may convey their cultural tastes and the social groups they admired. Because of the symbolic nature of the product endorsement behavior, we can expect that users largely rely on the decisions of their social connections in making endorsement decisions.

2.3.2 *Private versus Public Activities*

In contrast to online endorsements that are publically observable by others, there are also a class of activities, such as clicks, that are not observable by default. When an activity is conducted under the observation of others (it is defined as *public activity*), the person is likely to monitor and regulate his activity to convey a public image that is aligned with his/her ideal and socially acceptable self-image. When an activity is *private*, it is more likely utilitarian-driven. For example, when a consumption decision is perceived to be a private one, a person is more likely to choose comfort over style and to choose economical over status signaling. Prior research indicates that people sometimes make decisions differently when they expect others to form impressions of them based on the decisions made (Graeff 1996; Kettle et al. 2011; Ratner et al. 2002; Snyder 1987). Ratner et al. (2002) find that in the evaluation of hedonic products, the awareness of one's decision being observed by others causes the individual to incorporate more variety into their consumption decisions. Graeff (1996) suggests that increased self-monitoring is associated with a greater effect of image congruence (i.e., consistency between brand image and one's self-image) on consumers' evaluations of publicly consumed brands, but not privately consumed brands.

Social media platforms ask online users to share information about themselves, including the online activities they conduct, in exchange for free services and information shared by others. Despite the openness of social media platform, user activities such as clicks and purchases, remain private. We propose public and private activities be treated differently as they pertain to different consumption motives.

2.3.3 *Endorsements via the Social-cast Channel*

One of the main features of social shopping website is to connect consumers so that they collaboratively discover products. Social network allows product endorsements to travel from the endorser to his or her followers. A follower becomes aware of a product through the live stream of product endorsements by those they follow. Figure 2-2 depicts how a registered social shopper receives a list of recent product endorsements from people he or she is following.

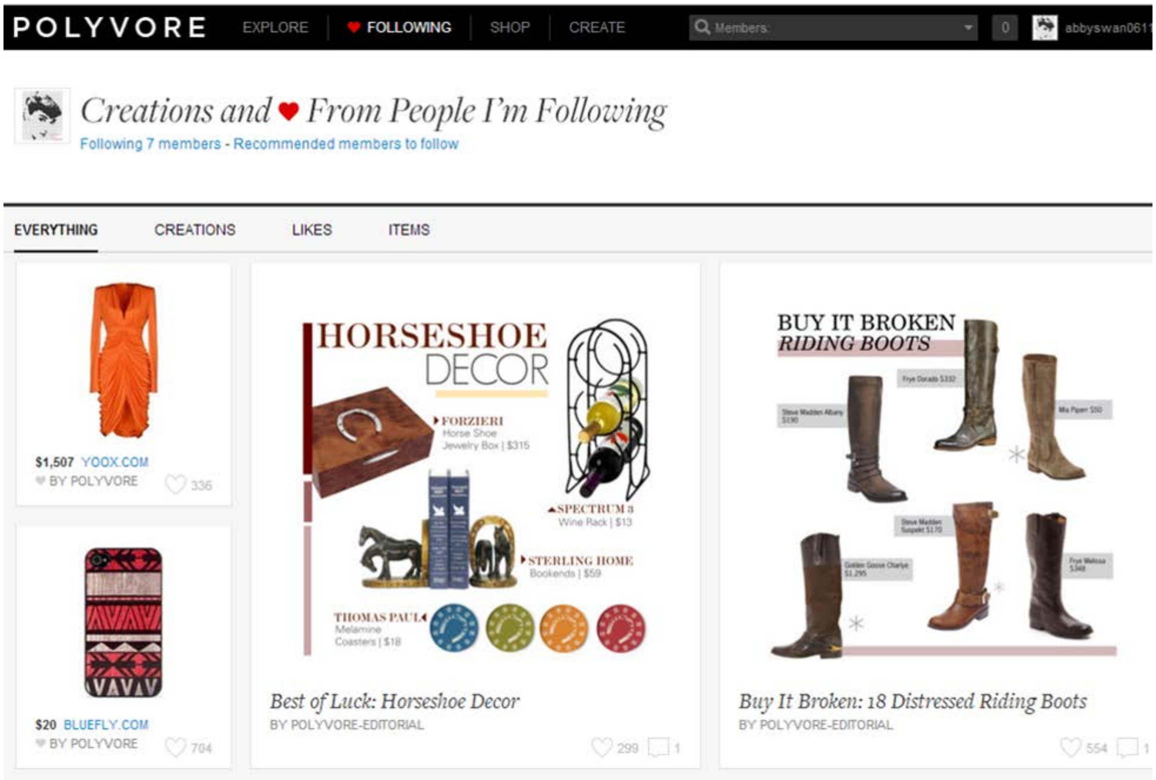


Figure 2-2 Product Endorsement Notifications from One's Followees

Unlike "friend" network, the "follower" network permits asymmetrical relationships, allowing a tie to exist even if only one person initiates it (Kane et al. 2014). Being a follower on social shopping websites means that the user subscribes to receive all the product endorsements from those the user follows. According to the informative social influence literature (Burnkrant et al. 1975; Deutsch et al. 1955), individuals may use the information provided by others as a source of the true value of the object under consideration. Burnkrant et al. (1975) find that after observing others evaluating a product favorably, people perceive the product more favorably themselves than they would have in the absence of this observation. Endorsements from the aspiration group provides a positive signal about the value of the product. Therefore, products endorsed by a person's aspiration group are more likely to be discovered and evaluated. Thus, we argue that,

H1: *The* <u>*more*</u> *friend endorsements a product receives in the current period, the* <u>*more*</u> *private examinations (clicks) it will get in the next period.*

Consumers make careful decisions when they are aware that their actions will be publicly visible (Ratner et al. 2002). They use two sources of information in making decision (Duan et al. 2009). One is their own information based on personal judgment and tastes. The other is the information derived from the decision of others. As people go to social shopping websites looking for product ideas, a person's followees can be considered as an aspiration group. According to identity-signaling model (Berger et al. 2007), users who receive endorsements from their aspiration group are more likely to endorsed the products themselves. Meanwhile, the normative social influence literature (Burnkrant et al. 1975; Deutsch et al. 1955) offers an additional explanation for endorsements to diffuse among connected individuals: according to the normative aspect of social influence, people align their attitude with that of the valued others to assimilate with their social groups. In social shopping context, the products endorsed by one's reference group, i.e., one's followees, symbolize the group's value and norm to which the individual subscribe to. One way to comply with the reference group and support its values is to endorse the products endorsed by members of the reference group. Thus, the amount of endorsement a product receives from the socialcast channel is proportional to the amount endorsers' social capital in terms of how many followers they have. This unique property of the socialcast channel allows us to separate the effect of endorsements via socialcast and broadcast channels. Thus, we hypothesize that,

H2: *The <u>more</u> friend endorsements a product receives in the current period, the <u>more</u> public endorsements (likes) it will get in the next period.*

As we described in the introduction section and , an endorsement travels through the socialcast channel provides two types of signals for the decision makers, the aggregated number of endorsements and the personalized friend endorsement messages. When a friend endorsement is distributed to the endorser's followers, it is often accompanied by the total number of endorsements the product received altogether. The latter provides additional information of a different nature. It is interesting then, how users combine the two sources of information, from a followee and from generic others, in their private and public behaviors.

When a product is endorsed both by member in and outside of one's social network, the uncertainty regarding the value and social desirability of the product is greatly reduced. This increases the chances that a user endorses the same product publicly. Because the substantial reduction in the uncertainty regarding the product, a user may rely less on his or her own information acquisition. This makes private examination activities such as clicking on the product to find out more details about the product more redundant (recall that one can "like" or purchase a product from links embedded in the product information card itself without necessarily checking out the details of the product. Therefore, we hypothesize that,

H3: When spread via the socialcast channel, the <u>more</u> crowd endorsements, the <u>less</u> private examination (clicks) it will get in the next period.

H4: When spread via the socialcast channel, the <u>more</u> crowd endorsements, the <u>more</u> public endorsement (likes) it will get in the next period.

2.3.4 *Endorsements via the Broadcast Channel*

Social endorsements such as likes are also used in another way, i.e., as the total number of endorsements of a product, displayed whenever a user encounters the product (via searching or browsing, see Figure 2-3). We call the latter a broadcast channel for distributing social endorsement information. Note that aggregate social endorsement can appear both in broadcast and social cast channels. In this subsection, we examine the effect of aggregate social endorsement distributed via the broadcast channel.

When a user faces uncertainty about a product's desirability, he or she may learn about it by observing the number of existing endorsements. This effect is known as observational learning (Banerjee et al. 2004; Bikhchandani 1998; Bikhchandani et al. 1992). The traditional online reviews and ratings, which are often presented in the aggregate form on product pages, are considered to engender an observational learning effect. According to the theory of observational learning, the more endorsements a product receives, the stronger signal it sends about the product's desirability, the more likely a user becomes interested in the product. Private examination of a popular product satisfies a person's curiosity for what is out there. When lack better information, a product popularity as measured by accumulative endorsements indeed provides some guidance for a person's explorative behavior. Plus, such an explorative behavior does not have any consequence on one's social image because of its private nature. Hence we would expect a product with more prior endorsements to receive more clicks.

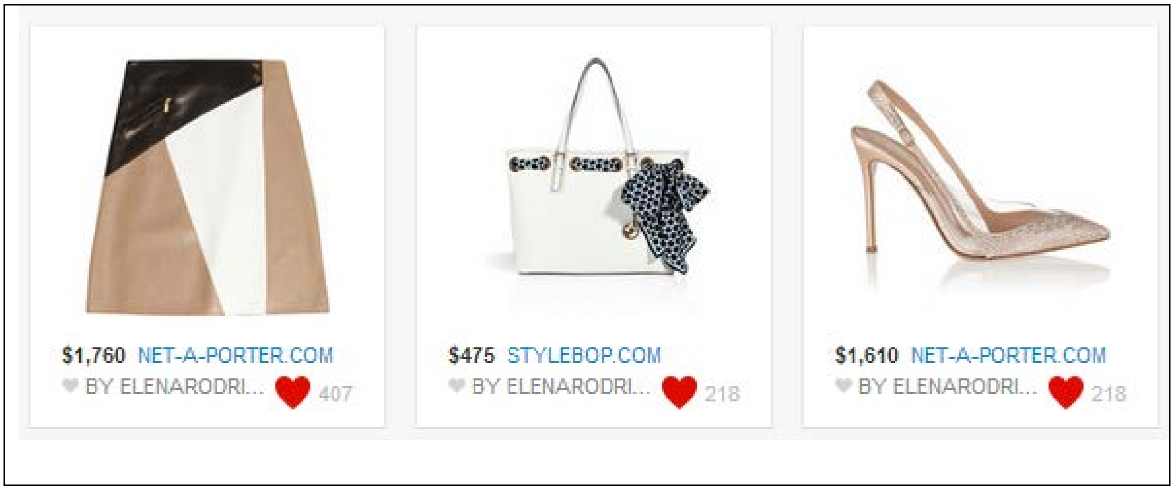


Figure 2-3 Products presented through broadcasting

H5: When spread via the broadcast channel, the more crowd endorsements, the more private examinations (clicks) it will get in the next period.

Endorsing a product, on the other hand, is much more thoughtful decision because, as we have mentioned earlier, liking is an act of public endorsement that symbolizes one's taste and identity in online social environment. This is especially true for social shopping users because they go to such websites to look for unique and inspirational product ideas that can distinguish and elevate themselves. This suggests that social shopping is a highly identity-involvement behavior. According to the identity-signaling model (Berger et al. 2007), when it comes to identity-involvement behaviors, people tend to converge with their positive reference groups (or aspiration groups) and diverge from negative reference groups (or avoidance groups). In the fashion literature in particular, trend setting groups distinguish themselves by deviating from the popular choices (Bikhchandani et al. 1992). When people follow the total number of likes in their explorative behaviors, they often end up not endorsing such a popular product they found because it came from an avoidance group rather than an inspiration group. Often times, such a product does not conform to the tastes and values the individual subscribes to and would undermine her social identity if she endorses it. Therefore, holding the endorsement from the socialcast channel constant, the more endorsement a product receives, the more likely it is deemed as coming from an avoidance group, the less desirable it is for the user to endorse the product. We thus hypothesize that,

H6: *When spread via the broadcast channel, the more crowd endorsements, the less public endorsements (likes) it will get in the next period.*

2.4 Empirical Approach

2.4.1 *Data*

We test our hypotheses using data collected from a leading US social shopping site dedicated to fashion, interior design and artistic expressions. As of August 2012, the website has over 17 million monthly unique visitors (Taylor 2012). This site allows members to curate personal collection of products from within the site or from external sources, and to create idea boards (called "sets") by mixing-and-matching different products.

Social networking features have a strong presence in the site's designs. Members can follow other members, like a product or a product set, and comment on it. They can also click on a link to view details about the product including product descriptions, similar items, etc.. They can also follow an external link associated with each product to a third party website to purchase the product. Despite being a young social shopping platform, it adds more than 4 million sets each month (Polyvore), suggesting a highly attractive social shopping community.

The products we collect are from two different product categories, one is tote handbags, and the other one is hair styling tools. According to previous literature (Berger et al. 2007; Midgley 1983), the consumption motivation of the former is more symbolic-oriented, while being more utilitarian-oriented for the latter. In Figure 2-4, we describe the related subjects stemmed from each product, and the crawling order from top to bottom.

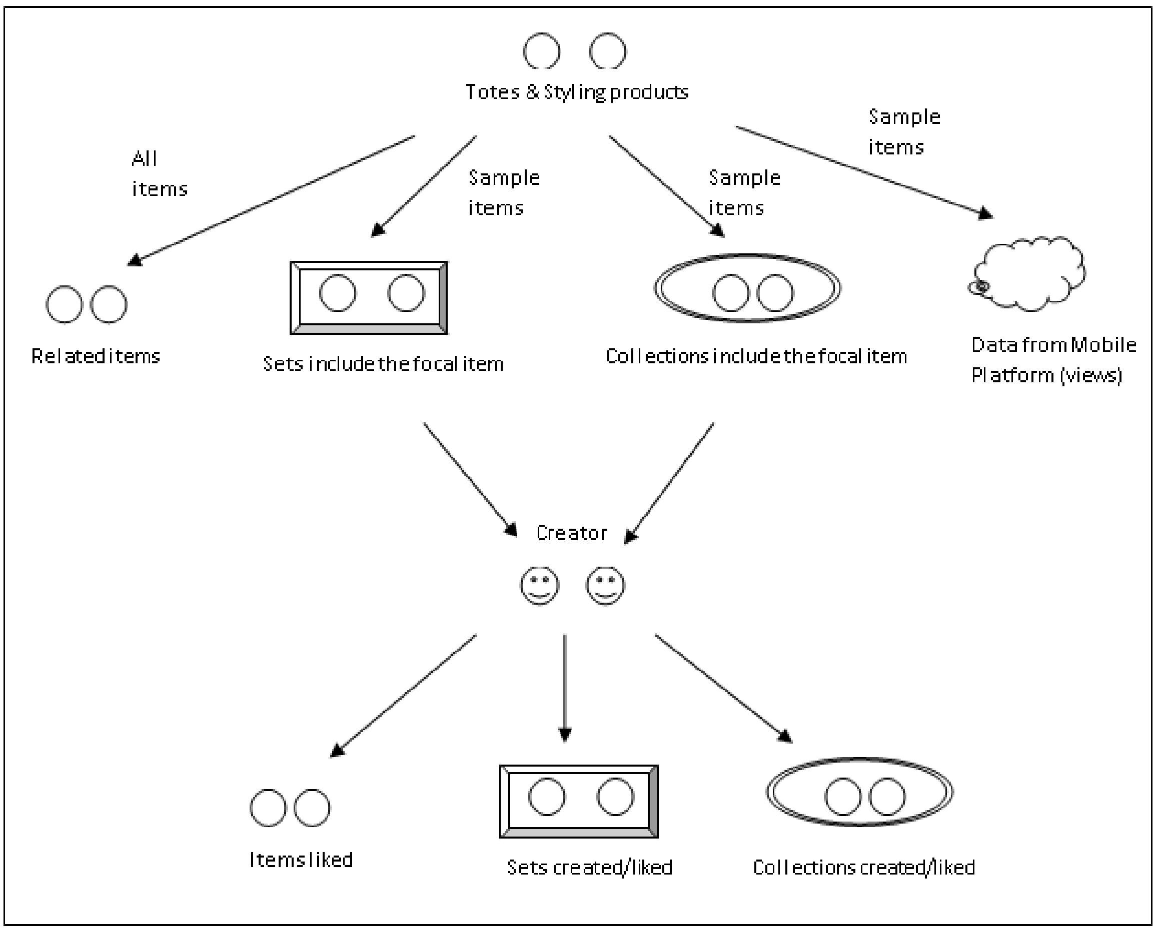


Figure 2-4 Crawling Process

We compile a panel of 1656 products and collect data related to these products every two weeks, starting from Sep 15th, 2013. One of the challenges we facing in data collection is the time window. We chose two weeks as our time window based on two considerations. First, we note that members may not check in every day. Endorsements by a follower from two weeks ago may still stay visible when the user logs on to the website. Second, due to the complexity of the data collection procedure, it is not practical to finish a round of data collection more frequently. Thirdly, a shorter time window may lead to sparseness of focal events (likes and clicks), increasing the noise in our statistical analysis. Our preliminary data collection also suggests there is adequate variation in bi-weekly data. So we went ahead to collect nine batches of data for a total time span of 18 consecutive weeks.

After deleting products with extreme number of clicks and likes, our sample contains a total of 934 tote handbags and 722 hair styling products[1]. The picture in Figure 2-5 describes a typical product webpage on the Polyvore platform. For each product, we collect basic product information (price, brand, category, discount, etc) and a history of social endorsements received, including likes and sets created, etc. We additionally collect information on set owners and likers of the product, including their social networks. For the dependent variables, we track the number of “clicks” and “likes” of a product. A stranger can also check out the list of products liked by a user from the user’s profile page. Therefore, we treat “like” as act of public endorsement. Similarly, set creation can also be viewed as an act of public endorsement, only that set creation requires more effort from

[1] The original sizes of the two product categories are different. To generate a similar sample size, we randomly selected ten percent of all tote handbags and kept all hair styling products. We also excluded products that were listed as sold out on the website.

the user. On the other hand, others users cannot see which products a user has clicked on a product to examine it further. It is worth noting that, without clicking, a user can see a simple information card of a product with a picture, the name of the product and the number of the cumulative likes. By clicking, a user can get further information about the product, including the source, the sets and collections that include the product, a list of likers of the product, and …. We therefore treat "click" as an act of private examination. It is also worth noting that a user can like a product right from the product information card without clicking through the product link. Therefore, clicking and liking can occur independently of each other. Our dataset includes 56,191 (focal and peripheral) products, 205,647 users, 33,764 sets, and 912,686 likes. In Appendix A, we present the variables used in this study.

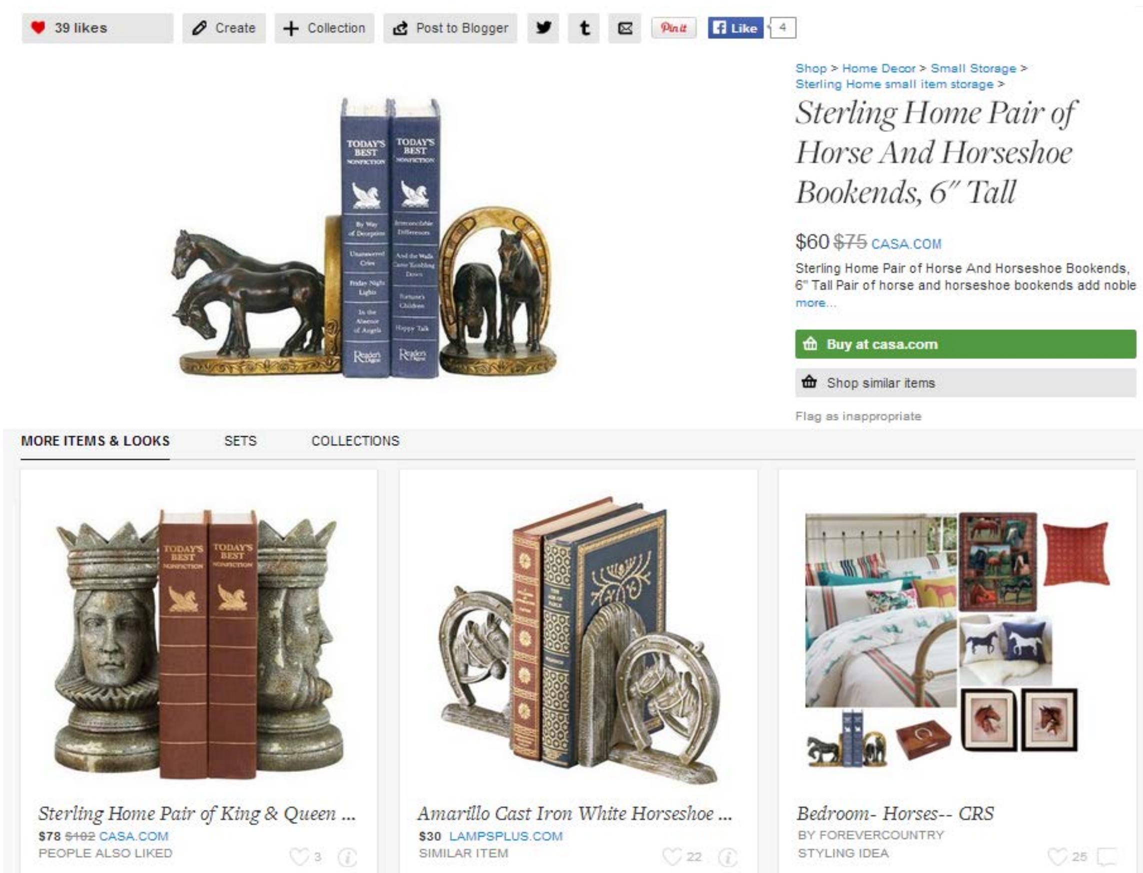


Figure 2-5 A Screenshot of Product Page

2.4.2 *Modelling Consumer's Decision: Private Examination*

We denote the cumulative clicks of a product i received up to the end of the t^{th} period as $Clicks_{it}$ (t = 1,2,3….9). Similarly, we define the cumulative likes of a product i received up to the end of the t^{th} period as $Likes_{it,}$ (t = 1,2,3….9). The lagged cumulative likes, $Likes_{it-1}$, reflects the aggregate endorsement before the t^{th} period and thus can be used to operationalize for measuring the observational learning effect.

A product's endorsements received during the $t\text{-}1^{th}$ period is shared with all the endorser' followers, so we calculate the number of endorsements broadcast during the $t\text{-}1^{th}$ period by adding up the number of the followers of the new endorsers. We calculated it as follows. The coefficients of $NewLikerFollower_{it-1}$ on $NewClicks_{it}$ estimate the effect of new social endorsements on product clicks of the next period.

Social capital theory suggests that networks of relationships constitute a valuable resource for the conduct of social affairs (Nahapiet et al. 1998). Network position is considered as one type of social capital, in which centrality is found to influence individual performance (Burt 2000). In other words, the social influence suggests that endorsers' social capital, in terms of the number of followers, matters in spreading social endorsements. Figure 2-6 portraits a two-step network for a product. As the example shows, the focal product is endorsed by four users, whom are followed by several other users. The higher the aggregated followers of the endorsers, the more the number of endorsements spread through the social channel.

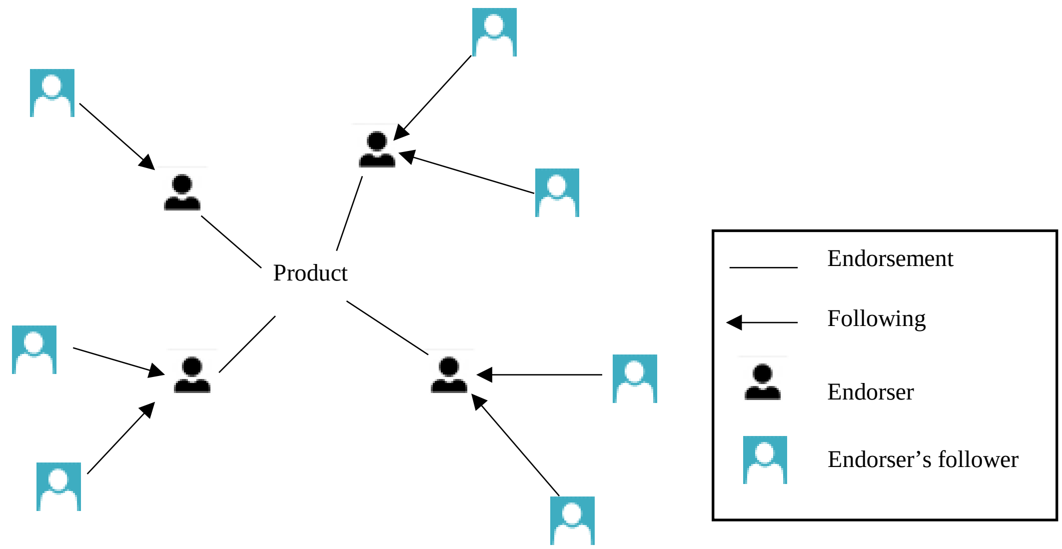
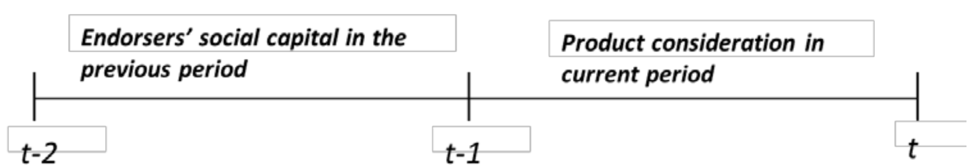


Figure 2-6 product endorsers and endorsers' followers

$$NewLikerFollower_{it-1} = \sum_{j=0}^{like_{it-1}} Follower_{ijt-1}$$

We also control for several alternative factors that contribute to the incremental clicks. One of the factors is the number of sets that include a certain product. To create a product set with a certain product can be considered as another form of product endorsement, whereby the product is mix-and-matched with other products.



Another factor we control is the computer recommendations. Computer recommendations are algorithm-generated, based on either product attributes or consumer co-purchase patterns, and offer consumers great convenience in discovering products. Previous research found that computer recommendations alter product visibility and thus demand (Oestreicher-Singer et al. 2008; 2012a; 2012b). Two types of computer recommendations exist on our social shopping platform, i.e., “similar items” and “people also liked”. These recommendations connect a focal product with numerous others, and form a product network. In hedonic browsing, people follow product links from one product to another. Hence, the more a product being listed as a similar or co-liked item of other products (i.e. incoming links), the more likely it will be visited by consumers. Following Oestreicher-Singer et al. (2012a), we use a product’s incoming eigenvector centrality to capture the relative connectivity of the product. Eigenvector centrality gives higher weights to links from a more central node. It captures the idea that a product can achieve a high connectivity by having either many incoming links, or a few links from highly central products (Bonacich 1987). We use $SimilarItem_{it-1}$ and $CoLiked_{it-1}$ to denote the eigenvector centralities of a product in the two types of computer recommendation networks.

It is natural to expect that other time-variant product attributes might also influence the number of clicks a product will receive, such as price, discount, and inventory level. We include those variables in our model. We also include a time variable, *Batchid,* to absorb common shocks during the bi-weekly data collection process. At last, ε_{it} is the unobserved disturbance term.

The model of private examination is described as follows.

$$Log(NewClicks_{it}) = \beta_0 + \beta_1 Log(Likes_{it-1}) + \beta_2 Log(NewLikerFollower_{it-1}) + \beta_3 Log(Likes_{it-1}) * Log(NewLikerFollower_{it-1}) + \gamma Controls_{it} + \varepsilon_{it} \qquad (1)$$

2.4.3 *Modelling Consumer's Decision: Public Endorsement*

We simultaneously model consumers' endorsement behaviours, i.e., likes and set creations, along with click behaviour. As more consumers clicked an item during the t^{th} period, the more endorsements the item is likely to receive during this period. In another word, the increase in the number of clicks brings in traffic of those who will potentially endorse the item. Thus, $NewClicks_{it}$ is a strong predictor of $NewLikes_{it}$.

As described in the clicks model, both social endorsements and computer recommendations can lead to more clicks. However, we expect social endorsements play a significant role in the generating subsequent endorsements, but not computer recommendations. Computer recommendations such as "similar items" and "also like" provide consumers a consideration set but does not very little to convey the desirability of a product.[2] On the other hand, social endorsements, either in aggregate or atomic forms, can provide information on others' valuation of the products, thus can influence subsequent endorsements decisions such liking.

We also control the effect of product diffusion process. The product diffusion literature suggests that the level of adoption on each software product is influenced by a product's current user base and the number of potential users (Bass 1969). Product diffusion theory has two implications. First, the larger the current user base, the higher the adoption rate of potential users can be. Second, the increases in user base create a counter force: with more and more users adopting the product, its number of potential users decrease (Duan et al. 2009). The Bass Diffusion Model has been widely used in

[2] "also like" may provide some basic screening based on aggregate endorsement information. But without further information such as how many people liked the product, consumers get very little information about the desirability of the product. Of course, future computer recommendations may present additional information to assist product evaluation, but we are limited to the rudimentary kind of computer recommendations that merely indicate the kind of recommendations they are.

marketing and economics for modeling diffusion (Bass 1969). Because the model contains both linear and nonlinear components, we thus add product age (Age_{it}) and the quadratic term of age ($AgeSQ_{it}$) into our empirical model to control for product diffusion. This method has also been taken in several other studies (Duan et al. 2009; Li et al. 2013).

We additionally control for time variant product attributes such as original price, discount and inventory, as we did in the private examination model.

$$Log(NewLikes_{it}) = \beta_0 + \beta_1 Log(Likes_{it-1}) + \beta_2 Log(NewLikerFollower_{it-1}) + \beta_3 Log(Likes_{it-1}) * Log(NewLikerFollower_{it-1}) + \beta_4 Log(NewClicks_{it}) + \beta_5 AgebyMonth_{it} + \beta_6 AgebyMonth_{it}\hat{}2 + \gamma Controls_{it} + \varepsilon_{it} \quad (2)$$

2.5 Data Analysis and Results

2.5.1 *Variables and Measures*

Table 2-1 provides a summary statistics of the variables. The average new clicks that a product received is about 67.5 ($e^{4.198}$), and the average new likes is about 1.4 ($e^{0.346}$). By average, about 5.25 ($e^{1.658}$) broadcasts of product endorsements are generated within one period, with a maximum value of 700,815. The average product age is 180 days, ranging from 23 to 383 days.

Correlations among the variables are reported in Appendix B. We also check the collinearity of the explanatory variables before conducting any analysis. For each variable, VIF is less than 10, and the average VIF of all variables is less than 6, suggesting collinearity is not a significant issue in the dataset.

Table 2-1 Data Description

	Means	Std. Dev.	Min	Max
$Log(NewClicks_{it})$	4.198	2.283	0.000	10.409
$Log(NewLikes_{it})$	0.346	0.679	0.000	5.159
$Log(NewSets_{it})$	0.149	0.380	0.000	3.526
$Log(Likes_{it-1})$	2.233	1.239	0.000	8.123
$Log(Sets_{it-1})$	1.169	1.234	0.000	5.740
$Log(NewLikerFollower_{it-1})$	1.658	2.876	0.000	13.460
$Log(NewCreatorFollower_{it-1})$	0.870	2.205	0.000	11.384
$Log(OriginPrice_{it-1})$	5.432	1.642	1.524	8.732
$Discount_{it-1}$	0.032	0.105	0.000	0.802
$AgebyMonth_{it}$	5.953	2.798	0.767	12.767
$PageRankColike_{it-1}$	0.001	0.001	0.000	0.023
$PageRankSimilar_{it-1}$	0.001	0.001	0.000	0.007
$Soldout_{it-1}$	0.249	0.432	0.000	1.000

2.5.2 *Data Analysis*

Given the panel structure of the data, we use a fixed-effect specification in this analysis, to eliminate any time-invariant unobserved heterogeneity in the explanatory variables. For the first dependent variable, $Log(NewClicks_{it})$, the explanatory variables are added into the model step-wisely. As shown in Table 2-3, we begin with including product price, product age and the time dummies in the very first model. We then add computer commendations, number of cumulative likes and sets, new endorsers' followers, and interaction terms in the following models.

For the second dependent variable, $Log(NewLikes_{it})$, as described in the conceptual model, part of the new likes is contributed by the new clicks that a product receives in the same period, i.e., $Log(NewClicks_{it})$. Combining the two equations in the empirical approach section, we notice that $Log(NewClicks_{it})$ is endogenous. To address the endogeneity issue, we introduce $PageRankSimilar_{it-1}$ as an instrumental variable, which describes a product's eigenvector centrality in the network of the computer-recommended similar items at time t-1. This variable is system generated, and directly influences clicks, but not endorsements. We then estimate the equations with Two-stage Least-Squares (2SLS). We summarize the findings in the following Table 2-2.

Table 2-2 Summary of Results

	$NewClicks_{it}$	$NewLikes_{it}$
$AgebyMonth_{it}$	-	+
$AgebyMonth_{it}$ ^2	+	-
$Log(Likes_{it-1})$	+	-
$Log(NewLikerFollower_{it-1})$	+	+
$Log(Likes_{it-1}) * Log(NewLikerFollower_{it-1})$	-	+

2.5.3 *Private Examination*

We start with interpreting the interaction term. The coefficient for the interaction term, $Log(Likes_{it-1}) * Log(NewLikerFollower_{it-1})$, is negative ($p<0.05$), indicating that the number of total endorsements attenuates the positive effect of social endorsements through the social-cast channel. This supports H3.

The coefficients of $Log(NewLikerFollower_{it-1})$ on $Log(NewClicks_{it})$ is positive ($p<0.001$), indicating that the more endorsements spread through the social channel, the more private examination a product will get in the next period. Therefore, H1 is supported. Moreover, the coefficient of $Log(Likes_{it-1})$ is also positive ($p<0.001$), we can infer that cumulative endorsement via broadcast is positively related with private examination. Thus, H5 is also supported.

Table 2-3 Panel Data Regression on *Log(NewClicks$_{it}$)*

	Model1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Log(DisplayPrice$_{it-1}$)	0.988*** (0.130)	0.985*** (0.128)	1.000*** (0.128)	0.971*** (0.127)	0.972*** (0.127)
AgebyMonth$_{it}$	-0.746*** (0.031)	-0.775*** (0.031)	-0.806*** (0.032)	-0.749*** (0.033)	-0.750*** (0.033)
AgebyMonth$_{it}$ ^2	0.021*** (0.002)	0.024*** (0.002)	0.024*** (0.002)	0.022*** (0.002)	0.022*** (0.002)
2b.batchid	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)
3.batchid	-0.085* (0.038)	-0.082* (0.038)	-0.084* (0.038)	-0.104** (0.038)	-0.105** (0.038)
4.batchid	-0.201*** (0.037)	-0.197*** (0.036)	-0.200*** (0.036)	-0.186*** (0.036)	-0.187*** (0.036)
5.batchid	-0.148*** (0.036)	-0.143*** (0.036)	-0.145*** (0.036)	-0.157*** (0.035)	-0.157*** (0.035)
6.batchid	0.225*** (0.037)	0.229*** (0.036)	0.227*** (0.036)	0.234*** (0.036)	0.234*** (0.036)
7.batchid	0.233*** (0.038)	0.236*** (0.038)	0.234*** (0.038)	0.223*** (0.038)	0.222*** (0.038)
8o.batchid	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)
PageRankColike$_{it-1}$		305.871*** (33.682)	294.840*** (33.844)	291.996*** (33.490)	293.245*** (33.488)
PageRankSimilar$_{it-1}$		658.780*** (43.622)	647.260*** (43.752)	631.612*** (43.323)	634.196*** (43.331)
Log(Likes$_{it-1}$)			0.346** (0.109)	0.271* (0.112)	0.309** (0.113)
Log(NewLikerFollower$_{it-1}$)				0.079*** (0.006)	0.113*** (0.017)
Log(Sets$_{it-1}$)				-0.100 (0.093)	-0.102 (0.093)
Log(NewCreatorFollower$_{it-1}$)				0.025*** (0.007)	0.026*** (0.007)
Log(Likes$_{it-1}$) *Log(NewLikerFollower$_{it-1}$)*					-0.012* (0.006)
Constant	2.382** (0.734)	1.942** (0.724)	1.271 (0.754)	1.316 (0.747)	1.249 (0.747)
R2 overall	0.021	0.063	0.109	0.120	0.120
R2 within	0.144	0.168	0.169	0.187	0.187
N	11592	11592	11592	11592	11592

* p<0.05, ** p<0.01, *** p<0.001

We summarized the findings in the following table.

Table 2-4 Hypotheses on Private Examination

H1: The more friend endorsements a product receives in the current period, the more private examinations (clicks) it will get in the next period.	Supported
H3: When spread via the socialcast channel, the more crowd endorsements, the less private examination (clicks) it will get in the next period.	Weakly Supported
H5: When spread via the broadcast channel, the more crowd endorsements, the more private examinations (clicks) it will get in the next period.	Supported

2.5.4 ***Public Endorsement***

The coefficients of $Log(NewLikerFollower_{it-1})$ on $Log(NewLikes_{it})$ is positive ($p<0.001$), indicating that the more endorsements spread through the social channel, the more endorsements a product will get in the next period. Therefore, H2 is supported. The coefficient for the interaction term, $Log(Likes_{it-1})*Log(NewLikerFollower_{it-1})$, is also positively ($p<0.001$) related with $Log(NewLikes_{it})$, indicating that when spread via the social channel, the more cumulative endorsements, the more endorsements it will get in the next period. This supports H4. Moreover, the coefficient of $Log(Likes_{it-1})$ is negatively related ($p<0.001$) with $Log(NewLikes_{it})$, suggesting that the number of cumulative endorsements is negatively related with next period's public endorsement a product will receive, when spread via the broadcast channel. Thus, H6 is also supported.

The coefficients of $Log(OriginPrice_{it-1})$ on $Log(NewLikes_{it})$ is not significant, suggesting that products price is not associated with new endorsements in the next period. Same with $Discount_{it-1}$. The coefficients of $AgebyMonth_{it}$ on $Log(NewLikes_{it})$ is positive, but the coefficients of the quadratic term of $AgebyMonth_{it}$ on $Log(NewLikes_{it})$ is negative, indicating that the increase rate of *Log(NewLikes*$_{it}$*)* increase in earlier periods, but then decrease over time.

Table 2-5 Panel Data Regression on *Log(NewLikes$_{it}$)*

	OLS	OLS_interact	2SLS	2SLS_interact
Log(OriginPrice$_{it-1}$)	-0.017 (0.042)	-0.019 (0.042)	-0.108 (0.057)	-0.107 (0.056)
Discount$_{it-1}$	0.187 (0.107)	0.185 (0.107)	0.270* (0.131)	0.264* (0.131)
Soldout$_{it-1}$	-0.032* (0.013)	-0.031* (0.013)	0.273*** (0.078)	0.260*** (0.077)
AgebyMonth$_{it}$	0.092*** (0.010)	0.093*** (0.010)	0.150*** (0.019)	0.149*** (0.019)
AgebyMonth$_{it}$^2	-0.000 (0.001)	0.000 (0.001)	-0.002* (0.001)	-0.002* (0.001)
Log(Likes$_{it-1}$)	-0.867*** (0.033)	-0.886*** (0.033)	-0.866*** (0.048)	-0.887*** (0.047)
Log(Sets$_{it-1}$)	0.082** (0.027)	0.084** (0.027)	0.125*** (0.036)	0.126*** (0.035)
Log(NewLikerFollower$_{it-1}$)	0.045*** (0.002)	0.038*** (0.002)	0.036*** (0.003)	0.029*** (0.004)
Log(NewCreatorFollower$_{it-1}$)	0.008*** (0.002)	0.007** (0.002)	0.007* (0.003)	0.005 (0.003)
Log(NewClicks$_{it}$)	0.062*** (0.003)	0.062*** (0.003)	0.224*** (0.041)	0.217*** (0.040)
batchid=2	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)
batchid=3	-0.003 (0.011)	-0.002 (0.011)	0.034* (0.016)	0.033* (0.016)
batchid=4	0.036*** (0.011)	0.037*** (0.011)	0.019 (0.013)	0.021 (0.013)
batchid=5	0.024* (0.011)	0.024* (0.010)	0.009 (0.012)	0.009 (0.012)
batchid=6	-0.003 (0.011)	-0.003 (0.011)	-0.042** (0.015)	-0.041** (0.015)
batchid=7	-0.024* (0.011)	-0.024* (0.011)	-0.066*** (0.016)	-0.064*** (0.016)
batchid=8	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)
*Log(Likes$_{it-1}$)**		0.044***		0.049***
Log(NewLikerFollower$_{it-1}$)		(0.006)		(0.009)
Constant	1.387*** (0.246)	1.413*** (0.245)		
R2 within	0.285	0.258		
Adjust R-squared	0.178	0.182		
N	11592	11592	11592	11592

* p<0.05, ** p<0.01, *** p<0.001

We summarized the findings in the following table.

Table 2-6 Hypotheses on public endorsement

H2: The more friend endorsements a product receives in the current period, the more public endorsements (likes) it will get in the next period.	Supported
H4: When spread via the socialcast channel, the more crowd endorsements, the more public endorsement (likes) it will get in the next period.	Supported
H6: When spread via the broadcast channel, the more crowd endorsements, the less public endorsements (likes) it will get in the next period.	Supported

2.6 Robustness Checks

2.6.1 *Diffusion Curve for individual product*

Recall that in the model of public endorsement, we control for the diffusion process, by adding product age ($AgebyMonth_{it}$) and it quadratic term ($AgebyMonth_{it}$^2). Since each product might have slightly different diffusion curve, we capture the disparity by adding an interaction term between individual product and product age. We thus add an interaction term between *ProductID* and $AgebyMonth_{it}$ into our models. We find very similar results after include this term, and all hypotheses are still supported. We thus do not present the results here again.

2.6.2 *Endorsement through set creation*

Another way of endorsing a product is through set creations. We model the new set created during the t^th period as follows.

$$Log(NewSets_{it}) = \beta_0 + \beta_1 Log(Likes_{it-1}) + \beta_2 Log(Sets_{it-1}) + \beta_3 Log(NewLikerFollower_{it-1}) + \beta_4 Log(NewCreatorFollower_{it-1}) + \beta_5 Log(Sets_{it-1}) * Log(NewCreatorFollower_{it-1}) + \beta_6 Log(NewClicks_{it}) + \beta_7 AgebyMonth_{it} + \beta_8 AgebyMonth_{it}^{\wedge}2 + \gamma Controls_{it} + \varepsilon_{it} \quad (3)$$

The results are presented in Table 2-7. The coefficients suggest that the more the sets made known to followers, the more new sets will be created in the next period. Also, the overall (via social and non-social channels) effect of the number of existing sets is negatively related with the number of sets created in the next period. But from the results, we cannot tell the separate effect via social and non-social channels, because the coefficient for the interaction term is not significant.

Table 2-7 Panel Data Regression on *Log(NewSets$_{it}$)*

	OLS	OLS_interact	2SLS	2SLS_interact
Log(OriginPrice$_{it-1}$)	-0.027 (0.032)	-0.026 (0.032)	-0.039 (0.037)	-0.039 (0.037)
Discount$_{it-1}$	0.051 (0.081)	0.052 (0.081)	0.062 (0.096)	0.063 (0.095)
Soldout$_{it-1}$	-0.043*** (0.010)	-0.043*** (0.010)	-0.003 (0.065)	-0.002 (0.065)
AgebyMonth$_{it}$	0.036*** (0.007)	0.036*** (0.007)	0.043** (0.014)	0.044** (0.014)
AgebyMonth$_{it}$^2	-0.000 (0.000)	-0.000 (0.000)	-0.001 (0.001)	-0.001 (0.001)
Log(Likes$_{it-1}$)	0.027 (0.025)	0.029 (0.025)	0.027 (0.037)	0.029 (0.037)
Log(Sets$_{it-1}$)	-0.655*** (0.021)	-0.659*** (0.021)	-0.649*** (0.049)	-0.653*** (0.050)
Log(NewLikerFollower$_{it-1}$)	0.005*** (0.001)	0.005*** (0.001)	0.003 (0.002)	0.003 (0.002)
Log(NewCreatorFollower$_{it-1}$)	0.007*** (0.002)	0.009*** (0.002)	0.007** (0.003)	0.009** (0.003)
Log(NewClicks$_{it}$)	0.013*** (0.003)	0.013*** (0.003)	0.034 (0.034)	0.035 (0.034)
batchid=2	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)
batchid=3	-0.013 (0.008)	-0.013 (0.008)	-0.008 (0.012)	-0.008 (0.012)
batchid=4	0.017* (0.008)	0.017* (0.008)	0.015 (0.009)	0.015 (0.009)
batchid=5	-0.031*** (0.008)	-0.031*** (0.008)	-0.033*** (0.009)	-0.033*** (0.009)
batchid=6	-0.012 (0.008)	-0.012 (0.008)	-0.017 (0.012)	-0.018 (0.012)
batchid=7	-0.022** (0.008)	-0.022** (0.008)	-0.028* (0.012)	-0.028* (0.012)
batchid=8	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)
Log(Sets$_{it-1}$) Log(NewCreatorFollower$_{it-1}$)*		-0.004 (0.004)		-0.004 (0.006)
Constant	0.756*** (0.185)	0.755*** (0.185)		
R2 within	0.248	0.249		
Adjust R-squared	0.118	0.118		
N	11592	11592	11592	11592

* p<0.05, ** p<0.01, *** p<0.001

2.6.3 *Symbolic versus non-symbolic products*

As we mentioned earlier, we collected data for two product categories, one is handbag and the other one is hairstyling tools. According to Midgley (1983), handbags have high symbolic value than hairstyling tools. We thus separate the original dataset by product categories to two samples. All our hypotheses hold on both types of products, see Table 2-10 and Table 2-11. The coefficient of $Log(Likes_{it-1})$ for handbags (-0.882, $p< 0.001$) is a little larger than that of styling tools (-0.835, $p< 0.001$), but the result of t-test suggests the two coefficients are not statistically different ($p=0.768$). This indicates that the negative effect of crowd endorsement is consistent for products with traditionally high and low symbolic values, suggesting that both products are suffered from the identity-signaling nature of public behaviors. This also confirms our suggestion on not treating symbolic and functional as two opposite product categories, since hair styling tools are traditionally considered as functional products, and consumption behaviors of those products were considered as less related with self-identity.

Table 2-8 Panel Data Regression on *Log(NewClicks$_{it}$)* for Handbags

	Model1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Log(DisplayPrice$_{it-1}$)	1.028*** (0.177)	0.785*** (0.174)	0.833*** (0.174)	0.813*** (0.173)	0.809*** (0.173)
AgebyMonth$_{it}$	-0.795*** (0.046)	-0.823*** (0.045)	-0.887*** (0.048)	-0.814*** (0.048)	-0.814*** (0.048)
AgebyMonth$_{it}$ ^2	0.009* (0.004)	0.010** (0.004)	0.012** (0.004)	0.009* (0.004)	0.008* (0.004)
2b.batchid	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)
3.batchid	-0.082 (0.058)	-0.081 (0.057)	-0.083 (0.057)	-0.109 (0.057)	-0.113* (0.057)
4.batchid	-0.216*** (0.056)	-0.209*** (0.055)	-0.215*** (0.055)	-0.217*** (0.054)	-0.223*** (0.054)
5.batchid	-0.261*** (0.055)	-0.251*** (0.054)	-0.257*** (0.054)	-0.281*** (0.054)	-0.284*** (0.054)
6.batchid	0.236*** (0.056)	0.247*** (0.055)	0.239*** (0.055)	0.227*** (0.055)	0.224*** (0.055)
7.batchid	0.153** (0.058)	0.156** (0.057)	0.148** (0.057)	0.129* (0.057)	0.127* (0.057)
8o.batchid	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)
PageRankColike$_{it-1}$		725.226*** (139.252)	685.258*** (139.383)	684.954*** (138.248)	679.361*** (138.162)
PageRankSimilar$_{it-1}$		2802.857*** (221.146)	2729.326*** (221.535)	2721.615*** (219.617)	2756.158*** (219.765)
Log(Likes$_{it-1}$)			0.652*** (0.157)	0.571*** (0.161)	0.635*** (0.163)
Log(NewLikerFollower$_{it-1}$)				0.078*** (0.008)	0.144*** (0.024)
Log(Sets$_{it-1}$)				-0.121 (0.131)	-0.119 (0.131)
Log(NewCreatorFollower$_{it-1}$)				0.021 (0.011)	0.023* (0.011)
Log(Likes$_{it-1}$) Log(NewLikerFollower$_{it-1}$)*					-0.024** (0.008)
Constant	1.432 (1.202)	2.735* (1.183)	1.256 (1.233)	1.279 (1.223)	1.194 (1.222)
R2 overall	0.038	0.077	0.141	0.152	0.153
R2 within	0.214	0.244	0.246	0.260	0.261
N	6538	6538	6538	6538	6538

* p<0.05, ** p<0.01, *** p<0.001

Table 2-9 Panel Data Regression on *Log(NewClicks$_{it}$)* for Styling Tools

	Model1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Log(DisplayPrice$_{it-1}$)	-0.293 (0.183)	-0.171 (0.176)	-0.169 (0.176)	-0.180 (0.174)	-0.179 (0.174)
AgebyMonth$_{it}$	-0.236*** (0.039)	-0.278*** (0.038)	-0.246*** (0.039)	-0.221*** (0.039)	-0.222*** (0.039)
AgebyMonth$_{it}$ ^2	0.002 (0.003)	0.005* (0.002)	0.005 (0.002)	0.005 (0.002)	0.005 (0.002)
2b.batchid	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)
3.batchid	-0.103* (0.042)	-0.101* (0.040)	-0.098* (0.040)	-0.104** (0.040)	-0.104** (0.040)
4.batchid	-0.221*** (0.040)	-0.218*** (0.039)	-0.215*** (0.039)	-0.181*** (0.038)	-0.181*** (0.038)
5.batchid	-0.082* (0.039)	-0.075* (0.038)	-0.073 (0.038)	-0.064 (0.037)	-0.063 (0.037)
6.batchid	0.126** (0.040)	0.134*** (0.038)	0.135*** (0.038)	0.168*** (0.038)	0.169*** (0.038)
7.batchid	0.278*** (0.042)	0.284*** (0.040)	0.284*** (0.040)	0.286*** (0.040)	0.286*** (0.040)
8o.batchid	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)
PageRankColike$_{it-1}$		276.013*** (24.706)	287.187*** (24.928)	282.518*** (24.584)	282.965*** (24.596)
PageRankSimilar$_{it-1}$		484.149*** (31.653)	496.069*** (31.840)	486.213*** (31.447)	486.881*** (31.468)
Log(Likes$_{it-1}$)			-0.396** (0.124)	-0.386** (0.129)	-0.372** (0.131)
Log(NewLikerFollower$_{it-1}$)				0.069*** (0.007)	0.080*** (0.019)
Log(Sets$_{it-1}$)				-0.250* (0.110)	-0.253* (0.111)
Log(NewCreatorFollower$_{it-1}$)				0.027*** (0.008)	0.027*** (0.008)
Log(Likes$_{it-1}$) Log(NewLikerFollower$_{it-1}$)*					-0.004 (0.007)
Constant	6.702*** (0.740)	5.507*** (0.717)	6.153*** (0.745)	6.221*** (0.738)	6.195*** (0.739)
R2 overall	0.020	0.137	0.000	0.001	0.001
R2 within	0.049	0.115	0.117	0.143	0.143
N	5054	5054	5054	5054	5054

* p<0.05, ** p<0.01, *** p<0.001

Table 2-10 Panel Data Regression on *Log(NewLikes$_{it}$)* for Handbags

	OLS	OLS_interact	2SLS	2SLS_interact
Log(OriginPrice$_{it-1}$)	-0.032 (0.047)	-0.033 (0.047)	-0.141 (0.072)	-0.135 (0.070)
Discount$_{it-1}$	0.218 (0.227)	0.197 (0.226)	0.900** (0.320)	0.828** (0.308)
Soldout$_{it-1}$	-0.035* (0.018)	-0.033 (0.018)	0.517*** (0.129)	0.483*** (0.124)
AgebyMonth$_{it}$	0.094*** (0.013)	0.094*** (0.013)	0.177*** (0.026)	0.172*** (0.026)
AgebyMonth$_{it}$^2	-0.001 (0.001)	-0.001 (0.001)	-0.004** (0.001)	-0.004** (0.001)
Log(Likes$_{it-1}$)	-0.870*** (0.042)	-0.885*** (0.042)	-0.882*** (0.064)	-0.900*** (0.063)
Log(Sets$_{it-1}$)	0.071* (0.034)	0.070* (0.034)	0.129** (0.048)	0.124** (0.046)
Log(NewLikerFollower$_{it-1}$)	0.039*** (0.002)	0.032*** (0.002)	0.027*** (0.004)	0.019*** (0.005)
Log(NewCreatorFollower$_{it-1}$)	0.013*** (0.003)	0.012*** (0.003)	0.011* (0.004)	0.010* (0.004)
Log(NewClicks$_{it}$)	0.054*** (0.004)	0.055*** (0.004)	0.288*** (0.054)	0.274*** (0.052)
batchid=2	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)
batchid=3	0.013 (0.015)	0.015 (0.015)	0.085** (0.027)	0.083** (0.026)
batchid=4	0.032* (0.014)	0.035* (0.014)	0.011 (0.019)	0.016 (0.018)
batchid=5	0.050*** (0.014)	0.051*** (0.014)	0.057** (0.017)	0.058*** (0.017)
batchid=6	0.026 (0.014)	0.027 (0.014)	-0.036 (0.022)	-0.030 (0.022)
batchid=7	-0.016 (0.015)	-0.015 (0.015)	-0.045* (0.020)	-0.042* (0.019)
batchid=8	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)
Log(Likes$_{it-1}$) Log(NewLikerFollower$_{it-1}$)*		0.046*** (0.007)		0.060*** (0.011)
Constant	1.619*** (0.336)	1.636*** (0.335)		
R2 within	0.231	0.212		
Adjust R-squared	0.181	0.187		
N	6538	6538	6538	6538

* p<0.05, ** p<0.01, *** p<0.001

Table 2-11 Panel Data Regression on *Log(NewLikes$_{it}$)* for Styling Tools

	OLS	OLS_interact	2SLS	2SLS_interact
Log(OriginPrice$_{it-1}$)	-0.020 (0.101)	-0.024 (0.101)	0.029 (0.098)	0.022 (0.098)
Discount$_{it-1}$	0.193 (0.122)	0.195 (0.121)	0.184 (0.156)	0.186 (0.156)
Soldout$_{it-1}$	-0.021 (0.019)	-0.022 (0.018)	0.085 (0.050)	0.079 (0.050)
AgebyMonth$_{it}$	0.086*** (0.016)	0.087*** (0.016)	0.095*** (0.017)	0.096*** (0.017)
AgebyMonth$_{it}$^2	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
Log(Likes$_{it-1}$)	-0.853*** (0.052)	-0.877*** (0.053)	-0.835*** (0.076)	-0.860*** (0.075)
Log(Sets$_{it-1}$)	0.087 (0.046)	0.096* (0.046)	0.119* (0.056)	0.126* (0.056)
Log(NewLikerFollower$_{it-1}$)	0.054*** (0.003)	0.048*** (0.003)	0.048*** (0.005)	0.043*** (0.005)
Log(NewCreatorFollower$_{it-1}$)	0.001 (0.003)	-0.000 (0.003)	-0.000 (0.005)	-0.001 (0.005)
Log(NewClicks$_{it}$)	0.088*** (0.007)	0.088*** (0.007)	0.187*** (0.044)	0.182*** (0.044)
batchid=2	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)
batchid=3	-0.023 (0.017)	-0.023 (0.017)	-0.007 (0.019)	-0.008 (0.019)
batchid=4	0.047** (0.016)	0.047** (0.016)	0.046** (0.017)	0.045** (0.017)
batchid=5	-0.008 (0.016)	-0.010 (0.016)	-0.021 (0.017)	-0.022 (0.017)
batchid=6	-0.037* (0.016)	-0.039* (0.016)	-0.054** (0.018)	-0.055** (0.018)
batchid=7	-0.040* (0.017)	-0.041* (0.017)	-0.074** (0.023)	-0.073** (0.023)
batchid=8	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)
Log(Likes$_{it-1}$) Log(NewLikerFollower$_{it-1}$)*		0.041*** (0.010)		0.040*** (0.015)
Constant	1.171*** (0.420)	1.207*** (0.419)		
R2 within	0.374	0.339		
Adjust R-squared	0.188	0.191		
N	5054	5054	5054	5054

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

2.7 Discussion and Concluding Remarks

In this study, we investigate the effect of previous endorsement on subsequent private examinations and public endorsements of a hedonic product. Private examination corresponds to a user clicking on a product to obtain more detailed information about the product, indicating that the user is aware of the product and would like to further examine it. Endorsements are publicly observable, and the act of endorsement indicates that consumers would like to share with others about his favorable evaluation of the product.

We find that sharing each individual product endorsement via the endorsers' social network brings attention to the product, in the form of more product examinations, and positive evaluation of the product, in terms of more product endorsements. We also find that adding another source of information, the number of cumulative endorsements, along with individualized social endorsement, generates less private examination but more public endorsement for the product. This is an interesting finding, which suggests that prior endorsements not only reinforce subsequent public endorsements as we learned in extant literature, but may also substitute private examination activities. For marketers and platform designers, this finding suggests that social shopping platforms should provide an easy way for consumers to endorse an item.

The studies of subsequent public activities are quite common, but the investigation on private activities is also non-trivial. Public activity is critical in transmitting information to major audiences, but it does not always reflect the true intention of the actor. On the other hand, private activity is a good indicator of personal behaviors in real life, such as a secret purchase, a malevolent conduct, etc..

In the consumption of symbolic products, observing the cumulative endorsements does not always encourage subsequent endorsements. In consistency with identity-signaling theory, we find that users align their public behaviors with their aspiration groups (the ones they follow), but not the rest. In contrast, users align their private behaviors with the majority, whether or not the majority is the crowd or friends.

This study contributes to a few literatures. First, to our knowledge, this is one of the first studies to investigate social endorsements in the social shopping context. Second, we separate the effects social influence and observational learning, and also study the interaction effect of the two. Thirdly, we also add to the literature of social influence and observational learning, by pointing out the public and private nature of the follow up actions. Forth, we contribute to the literature on user-generated content (UGC). Social endorsements often take the form of user-generated content and spread through online social networks, this research also holds important implications for other social media and user generated content (UGC) applications. Social networking features are found to affect user adoption decisions under several online social media contexts such as YouTube (Susarla et al. 2012), Facebook (Goh et al. 2013), Flickr (Zeng et al. 2013), etc. An important contribution we bring to social media and UGC literatures is that we examine and highlight the role of social endorsements for the consumption of symbolic products in a hedonic shopping environment. Even though the context of our study highlights the symbolic aspect of product evaluation, we argue that the insights we obtain can be applied to other online social systems as they often require consumers to reveal their preferences publically in exchange for “social" services.

For practitioners, the power of social shopping websites should be recognized and harnessed to market their businesses and build brand reputation. The study provides a theoretical framework for marketers to think about the value of social endorsements. We highlight that social endorsements can have two kinds of effects: observational learning and social influence. Our study establishes the significant value of social endorsements for marketers, especially when they are transmitted through social network of endorsers.

Our results hold valuable insights on two popular metrics, clicks and likes, on social shopping and other social networking sites. The marketers often compare the former to “click-through-rates” in non-social advertising and the later to “engagement.” We suggest that clicks and likes are not two successive stages of purchase funnel as many marketing literatures would suggest. Rather they are characteristically different due to the “public” nature of likes and the “private” nature of clicks. Our results highlight that the value of likes may be much more due to the “mega-phone” effect of social cast. Not only the number of likes, but also who like the product, matter. Moreover, our results imply that the click-through rate may not be perfectly aligned with customer interests or favorable opinions (e.g. likes). High click through rate may signal value uncertainty and may not be always a good thing for marketers. Rather than endless pursuit of click through rates or “engagements”, marketers should combine these different metrics and carefully interpret them. For example, a high number likes together with a low click through rate may signal that “blind herding” rather than sincere interests may be taking place.

This paper also helps marketers understand the effect of social endorsements at the presence of other marketing efforts, such as media exposures. By highlight the different effect of social endorsements on public and private behaviors, we attempt to provide some guidelines for marketers to manage and promote their products on social shopping platforms.

This paper can be improved in several ways. First, we can test the interaction between social endorsements and price. Second, a Panel Vector Autoregressive (PVAR) model estimation can be conducted for dealing with co-evolvement of dependent variables. Thirdly, further study can focus on understanding the motivations of social endorsements, be it self-expressive or instrumental (Solomon et al. 1987), or to extend support to their connections. Those motivations might differ between friend-type and follower-type social networks. Also, similar study can be conducted on other social media communities, to see if the results still hold.

Chapter 3. Friend Recommendation, Crowd Recommendation and Value-Expressive Evaluative Attitude

Social Endorsement is an important source for computer recommendation systems. Social endorsements are utilized by recommendation systems in two ways, disaggregated (or friend endorsement) and aggregated (or crowd endorsement). In this chapter, I discuss the impact of friend and crowd endorsement in the context of symbolic product consumption. I point out how consumers' value-expressive evaluative attitude moderates the impact.

3.1 Recommendation Systems

Computer recommendations gained popularity with the first wave of e-commerce. They are algorithm-generated, based on either product attributes or consumer co-purchase patterns, and offer consumers with advices in discovering and evaluating products. By providing product advice based on user-specified preferences, a user's purchase history, or choices made by other consumers with similar profiles, computer recommendations have the potential to reduce consumers' information overload and search complexity, and improve decision quality (Xiao et al. 2007).

3.2 Computer Recommendation and Social Endorsement

Similar to other information systems, a typical recommendation system consists of three major components (See Figure 3-1): *input* (e.g., user preferences, purchase history, other people's behavior and opinions), *process* (algorithm by which recommendations are generated), and *output* (where recommendations are presented to the user).

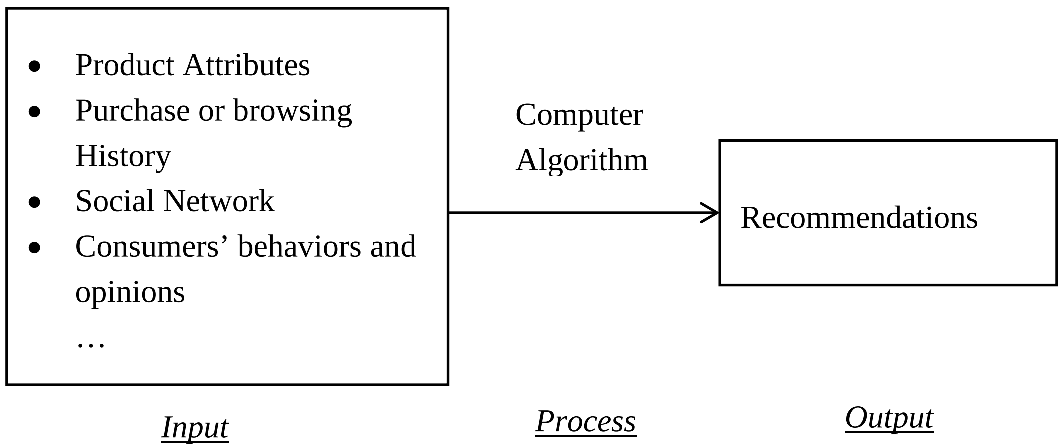


Figure 3-1 Recommendation System as a Type of Information System

Social endorsements, which denote consumers' favorable opinions towards a product shared among connected peers, can be collected from social media websites and be used as an information source of recommendation systems. Social endorsements are utilized by recommendation system in two ways, i.e., disaggregated and aggregated. Disaggregated social endorsement recommendation provide friends' preferences individually. We name such an endorsement as *friend recommendation*. Aggregated social endorsement recommendation is another type of computer recommendation which provides product recommendation based upon collective endorsements and is removed of social cues. We call it *crowd recommendation*. Table 3-1 illustrates the differences among three concepts: product review, friend recommendation, and crowd recommendation.

Table 3-1 Product Review, Friend Endorsement and Crowd Endorsement

	Without Social Cues	**With social cues**
Disaggregated	Anonymous reviews	Peer-to-peer recommendations (passive/active)
Aggregated	Recommendations based on group behavior	

3.3 Theoretical Development

In the following section, we argue that the impact of friend and crowd endorsements on symbolic goods consumption is moderated by consumer's evaluative attitude during the shopping process.

3.3.1 *Value-Expressive Evaluative Attitude*

The functional theory of attitudes suggests that individuals may have very different attitudes towards a product and each type of attitude is associate with a distinct value functions (Katz 1960). The value function is value expressive when the consumer believes that the ownership of a product reveals information about his or her identity, values, or beliefs to other people, and is utilitarian when the product is seen as merely providing functional or performance-related benefits (Katz 1960; Shavitt 1992).

Symbolic products are a type of products which are prominent in their intangible, symbolic and aesthetic attributes. The purchase of symbolic item might involve consumer motivations different from those associated with durable products and hence possibly different information-seeking patterns (Midgley 1983; Olshavsky et al. 1979).

Specifically, Midgley (1983) points out that the purchase of products whose primary purpose may be social is likely to invoke the search for information from other individuals rather than objective or impersonal sources. When shopping for those products, a consumer who holds a high value-expressive evaluative attitude will most care about the symbolic value of the product, and about how his adoption of the product will be perceived by others. When a friend of such consumer adopts a product, he may consider the adoption action as a hint that the friend is supporting this product and the product is desirable and acceptable in his social network. This reinforces his belief of adopting the product.

Conversely, consumers who hold a less value-expressive attitude evaluate a product by seeking information from both personal and objective sources, and put less weight on friend's opinions. We thus hypothesize that,

H1: *When shopping for symbolic goods, consumers who hold a higher value-expressive attitude are more likely to choose a product endorsed by a friend.*

On the other hand, according to Berger et al. (2008), when a product is adopted by the majority, its symbolic value is blurred. An example given by Berger et al. (2008) is the wearing of T-shirts. A T-shirt emblazoned with the name of a heavy metal rock band may facilitate interactions with people who like heavy metal music. But if all people start wearing such T-shirts because they look good with black jackets, the T-shirts will no longer be an effective signal. For people with high level of value-expressive demands, a product that has already been adopted by the majority others is less favourable. Thus, when receiving a crowd recommendation of a product, people with high value-expressive attitude is less likely to adopt the product. Therefore, we hypothesize that,

H2: *When shopping for symbolic goods, consumers who hold a* <u>*higher*</u> *value-expressive attitude are* <u>*less*</u> *likely to choose a product endorsed by the crowd.*

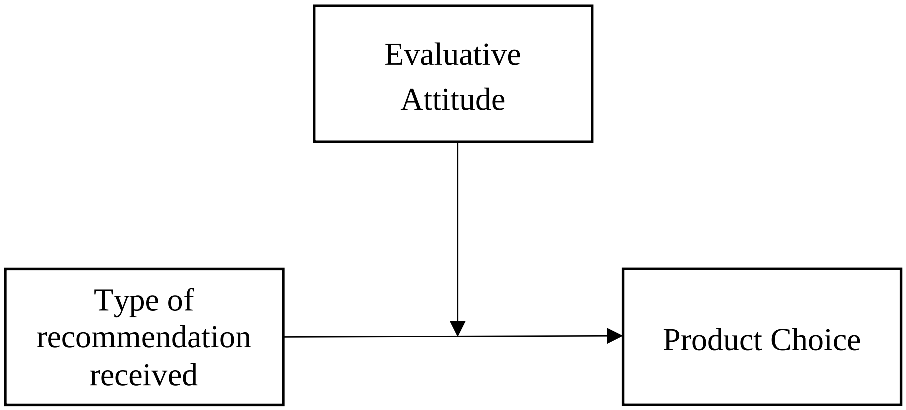


Figure 3-2 Research Model Showing the Interaction Effect

3.4 Research Methodology

We recruited subjects from a university subject pool to participate to study the effect of friend and crowd recommendations. Because our proposed mechanism requires the existence of past relationships, we asked each participate to recruit an experiment buddy to this study as Ill. These two then formed a "group" for the purpose of the study. When they reported to the study, participants from the same group were assigned with separate seats, so that they cannot communicate with each other during the experiment.

3.4.1 *Experiment Design*

The experiment study started with background information. Participants were asked to report their gender, GPA, age, status, etc. They also reported their relationship with their experiment buddy, using a scale ranging from *stranger* (1) to *very close friends*

(5). The experiment had two phases. In the first phase, to set up the study, participants were asked to make a series of choices between pairs of smartphone cases. Those decision tasks were *without* any recommendations. After they finish the first phase, there was a screen prompt saying that "the system is preparing for another group of decision tasks, please wait until all participants finish the tasks". The task in the first phase was not related with the experiment data we used in analysis, but was used to give participant an illusion that the recommendations in the second phase was generated upon the data collected in this earlier phase.

During the second phase, each participant was asked to assess several pairs of posters and choose one from each pair which they would like to use to decorate their dormitory. Posters were used in this experiment because posters are considered as a type of products that can reflect a person's cultural taste (Berger et al. 2007). Each participant was assigned with all the five conditions in random orders. Under each condition, they were asked to make a decision between two posters, and also indicate the similarity of the two posters as a manipulation check. To prevent contamination of the results, each condition includes either crowd recommendation or friend recommendation, or neither. One condition, condition 5, was used as a control group. Figure 3-4 demonstrates the condition where a participant receives a crowd recommendation on the second product.

We asked eight graduate students to evaluate the posters to make sure they are gender-neutral. A whole list of the posters can be found in in Appendix C.

Table 3-2 Experimental Manipulation

	Product A (Focal)	Product B (Alternative)
Crowd Recommendation	**C+**: most people in this experiment chose A	**C-**: most people in this experiment chose B
Friend Recommendation	**F+**: your experiment buddy chose A	**F-**: your experiment buddy chose B
*** NA**: without any recommendations		

Treatments were administered using a 5*5 Latin Squares design (see Figure 3-3), which is performed by placing participants in groups and presenting conditions to each group in a different order (Kempthorne 1952; MacKenzie 2002). This is also known as counterbalancing. Such design overcomes the shortcoming of order effect and increases efficiency.

T1	T2	T3	T4	T5
T2	T3	T4	T5	T1
T3	T4	T5	T1	T2
T4	T5	T1	T2	T3
T5	T1	T2	T3	T4

Figure 3-3 A 5*5 Latin Squares experiment design

At the end of experiment, participants were asked to indicate the attitude they hold while evaluating the posters, specifically whether he or she holds a utilitarian or value-expressive evaluative attitude.

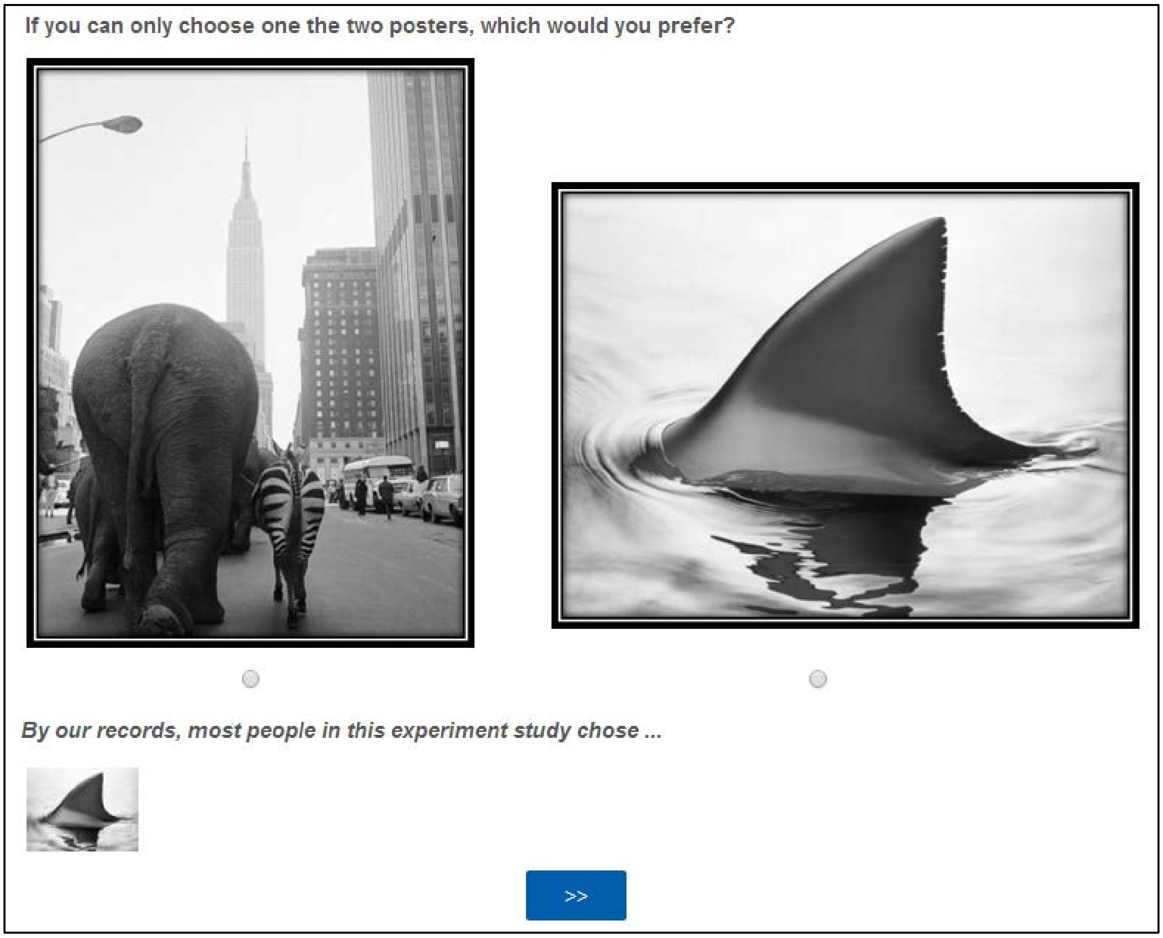


Figure 3-4 Experiment screenshot

3.4.2 *Measure - Evaluative Attitude*

While previous studies have divided evaluative attitudes into two opposing categories: value expressive and utilitarian, the line is not always clear. For instance, a person can evaluate a handbag by how its brand or appearance tells about the owner's belief and status, and he can also cares about how roomy the handbag is for holding stuffs. One may hold a high or low value-expressive evaluative attitude, but a low value-expressive evaluative attitude is not necessary related with a high utilitarian attitude. With such concerns, in this paper, we evaluate a person's evaluative attitude by the level of his value-expressive tendency.

Evaluative attitude refers to a customer's attitude toward to a product, specifically whether a consumer holds a utilitarian or value-expressive evaluative attitude. Self-image effects have been measured in other studies (Bearden et al. 1989; Johar et al. 1991; Smith et al. 2011). However, those scales are designed for contexts not relevant for this study. Candidate items were therefore tailored to assess a consumer's attitude to a specified product in this study, as shown in Table 3-3. Scores from these operationalized measures indicate whether an attitude is value-expressive or utilitarian. An extremely high score indicates that the value of a given product to a particular person stems entirely from symbolic product values. Extremely low scores mean that value is utilitarian in nature, driven by functional characteristics. Between there extremes, both attitude types influence the customer's decision to some degree.

Table 3-3 Theoretical Dimensions of Evaluative Attitude Items

Measure	Items
Evaluative Attitude (Johar et al. 1991; Smith et al. 2011)	Now please tell us a little bit more about your evaluation criteria.- • I would hang posters as a form of self-expression. • I would hang posters as a statement of my taste. • I would choose a poster based on what it tells others about me. • The poster I would choose has a lot to do with how I would like other people to think about me.

3.5 Results

3.5.1 *Participants*

Out of the 168 subjects who have reported to this experiment study, we obtained 154 usable samples after delete fourteen subjects who cannot correctly indicate their experiment buddies' names, or whose experiment buddies cannot correctly point out their names, and those who reported their friendship type as stranger. Participants' age averaged 21, ranging from 18 to 32. Participants included 68.8% men and 31.2% women, reflecting the gender composition of upper-division business students at the college. The average self-reported GPA was 3.75 out of 5, ranging from 2.0 to 5.0. Most participants (60.1%) are in their third year of college study. They also indicate their perceived friendship type with the experiment buddy: very close friend (54.55%); good/close friend (29.87%); regular/casual friend (12.34%); and acquaintance (3.25%), out of all subjects. Also, 70.1% of the experiment pairs reported exactly the same friendship type. The rest of the pairs were slightly different in friendship perception, but none of them has reported a discrepancy larger than 1. Thus, the report of perceived friendship was with high accuracy. Our random assignment of participants led to the sample sizes in each treatment condition as shown in Table 3-4. The result of symmetry testing (p=0.678) indicates there is no evidence to say this Latin square is asymmetric; that is, this distribution of the conditions is balanced.

Table 3-4 Cross-tabulation of Recommendation * Product Pair

Sample Size		Condition					Total
		1	2	3	4	5	
Product pairs	1	35	32	29	28	30	154
	2	38	19	34	38	25	154
	3	34	32	31	26	31	154
	4	32	26	25	38	33	154
	5	40	26	32	32	24	154
Total		179	135	151	162	143	770

3.5.2 *Manipulation Check*

We obtain participants perceptions of the similarity between the two posters in each pair, to make sure that the recommendations will have an impact on the participants. As we described in the experiment design part, we asked the subjects to evaluate the similarity between the two posters on a seven-point Likert-type scale ranging from *very different* (1) to *very similar* (7). We do not want the participants feel the posters are too similar nor too different. If they are too similar, the decision might be merely a guess. On the other hand, if the posters are too different, the impact of the recommendations could be negligible. Our data indicate that the posters are neither too similar nor too different (similarity ranges from 2.58 to 3.98 for the five pairs), suggesting our recommendations could have an impact on subjects' decisions.

3.5.3 *Measurement*

After calculate the factor loadings of the evaluative attitude variable, we exclude one item (EA4) with loading less than 0.5 on the basis that even where an item was justified theoretically, a low loading indicates that the item (1) may not have been interpreted as intended and (2) would add little or no explanatory power, and potentially even bias estimates (Chen et al. 2007; Smith et al. 2011).

Table 3-5 Factor Loadings on Evaluative Attitude

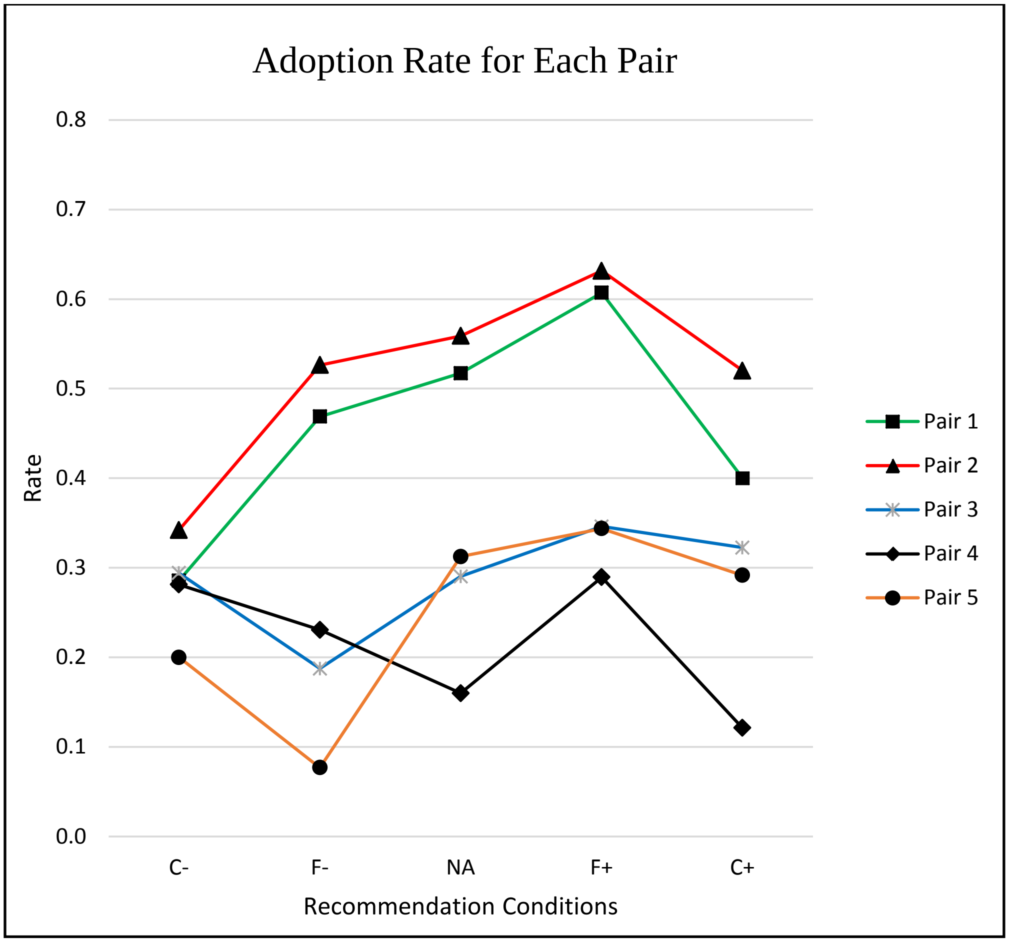
Measure	Evaluative Attitude	Loadings
EA1	I would hang posters as a form of self-expression.	0.777
EA2	I would hang posters as a statement of my taste.	0.823
EA3	I would choose a poster based on what it tells others about me.	0.694
EA4	The poster I would choose has a lot to do with how I would like other people to think about me.	0.386
Note. Only EA1, EA2, EA3 are used in analysis		

3.5.4 *Test of Hypotheses*

We start with calculating the adoption rate for each product pair, and present them in

Figure 3-5. From this figure, we can tell a few patterns of the recommendation effect. First, for the first two pairs, the adoption rate of condition 3 is about 0.5. That is, when there is no recommendation provided, the products in the first two pairs are about equally popular among the subjects. On the contrary, for the last three pairs, when receive no recommendations, one product is significantly more popular than the other. Since we use the condition of no recommendation as the baseline, we study the evenly-popular pairs and non-evenly-popular pairs separately.

For the first two pairs, receiving a friend recommendation increases a product's chance of being selected by the subjects, as condition 4 denotes a friend recommendation the first product within a group and condition 2 for the second product. Also, receiving a crowd recommendation (condition 5) decreases the chance of being selected. For the last three pairs, still, receiving a friend recommendation seems to increase a product's chance of being selected. No strong pattern is shown for receiving crowd recommendations.



Note. For the sake of clarity, we only display one product of each pair.
Products chosen: 1-B; 2-B; 3-A; 4-B; 5-A

Figure 3-5 Adoption Rates of the Poster Pairs

ProductID	1	2	3	4	5
1	0.60	0.39	0.48	0.53	0.71
2	0.29	0.47	0.52	0.61	0.40
3	0.48	0.37	0.44	0.47	0.66
4	0.34	0.53	0.56	0.63	0.52
5	0.29	0.19	0.29	0.35	0.32
6	0.68	0.65	0.71	0.81	0.71
7	0.88	0.71	0.84	0.77	0.72
8	0.28	0.23	0.16	0.29	0.12
9	0.20	0.08	0.31	0.34	0.29
10	0.71	0.66	0.69	0.92	0.80
Grand Total	**0.46**	**0.43**	**0.50**	**0.57**	**0.54**

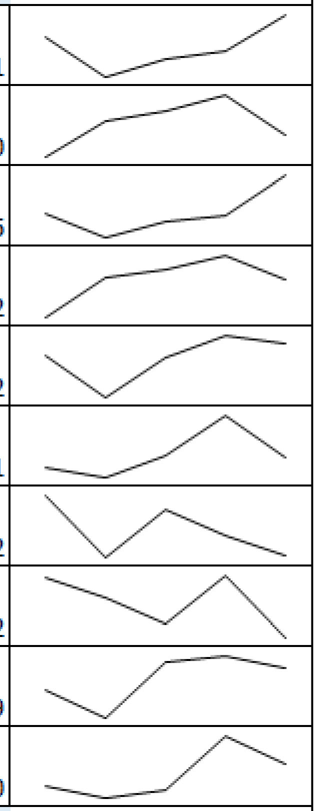


Figure 3-6 Adoption Pattern for Each Product

We build a logistic regression model as follows, and test the hypotheses for the evenly-popular pairs and non-evenly popular pairs separately.

$$logit(p) = \log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 Rec + \beta_2 EA + \beta_3 Rec * EA + \gamma Controls + \varepsilon$$

Since an interaction term is presented in this regression, we use marginal effect plot to show the results. In total, we have ten products from five comparison groups. We divide them into two unevenly popular groups and three evenly popular groups. For the effect of crowd recommendation (see Table 3-6), we find significant effect on the two evenly popular groups, but not on the unevenly popular ones. Also, products on different sides exhibit opposite patterns. For products listed on the left side of the webpage, crowd recommendation enhances adoption rate when the value-expressive evaluative attitude is larger than 2. Conversely, for products presented on the right side of the webpage, crowd recommendation reduces adoption rate when the value-expressive evaluative attitude is larger than 2.5. As shown in Figure 3-7, the odds ratio for the interaction term on crowd recommendation is 0.558 (p=0.027), suggesting that the ratio of the two odds ratios (high Evaluative Attitude over low Evaluative Attitude) is less than one. That is, there is a negative interaction between Crowd Recommendation and Evaluative Attitude. Thus, H2 is weakly supported for the first two pairs of products.

Figure 3-7 Logistics Regression for Products in Evenly Popular Pairs

Logistic regression — Number of obs = 118; LR chi2(5) = 11.73; Prob > chi2 = 0.0386; Log likelihood = -75.924244; Pseudo R2 = 0.0717

decision	Coef	Odd Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Rec	0.985+	2.678	0.577	1.71	0.088	-0.147	2.116
EA	2.716*	15.116	1.108	2.45	0.014	0.545	4.887
Rec_EA	-0.583*	0.558	0.263	-2.21	0.027	-1.099	-0.067
male	0.114	1.121	0.451	0.25	0.800	-0.769	0.998
friendshiptype	-0.332	0.718	0.235	-1.41	0.159	-0.793	0.130
_cons	-3.398	0.033	2.673	-1.27	0.204	-8.638	1.841

$^{+}$ p<0.1, * p<0.05, ** p<0.01, *** p<0.001

From descriptive analysis, the adoption rate increases when receiving a friend recommendation. Such increase holds for all ten products. However, we did not find statistical support for the interaction between friend recommendation and evaluative attitude (see Table 3-7), since the upper and lower bounds of the confidence interval are always on different sides of the zero line. Thus, H1 is not supported.

Table 3-6 The Marginal Effect of Crowd Recommendation

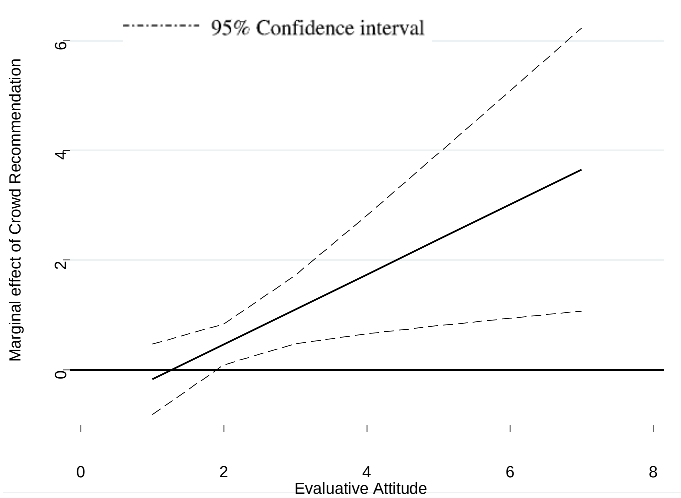
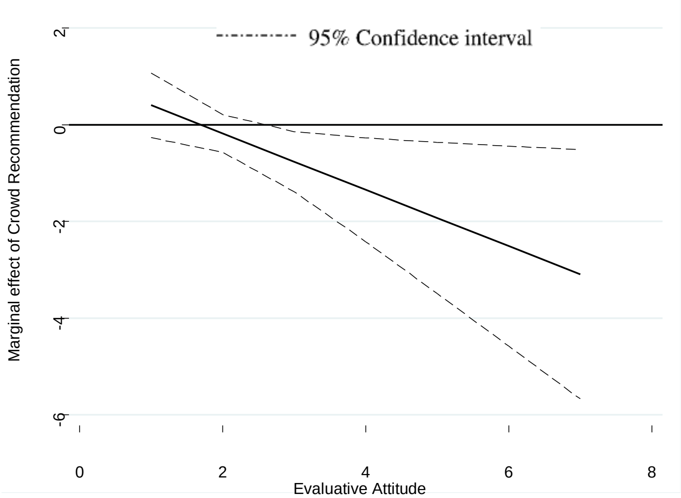
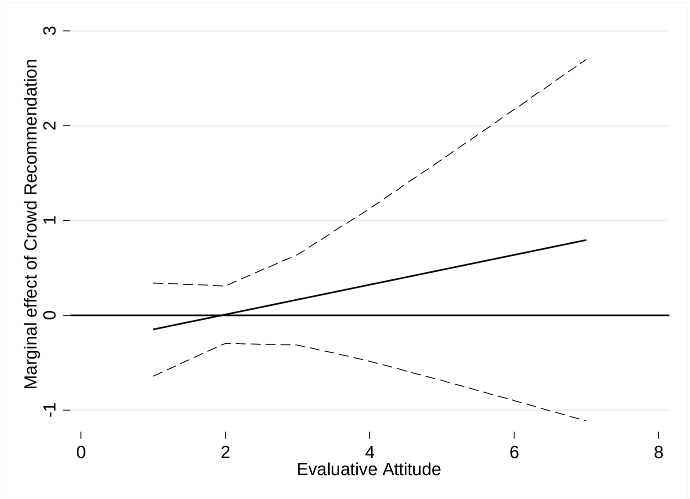
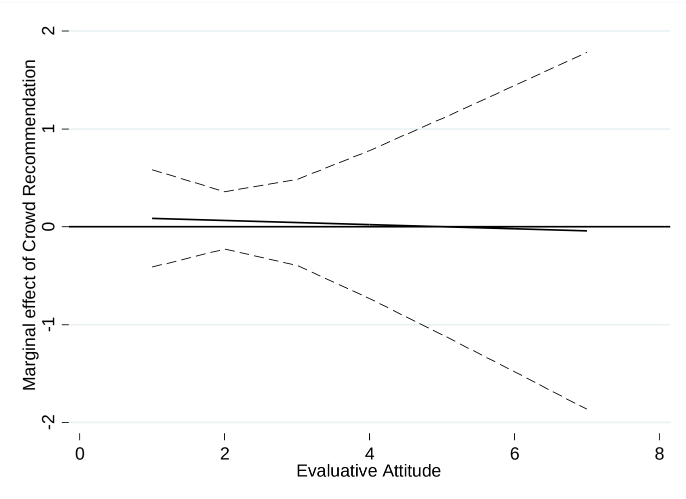
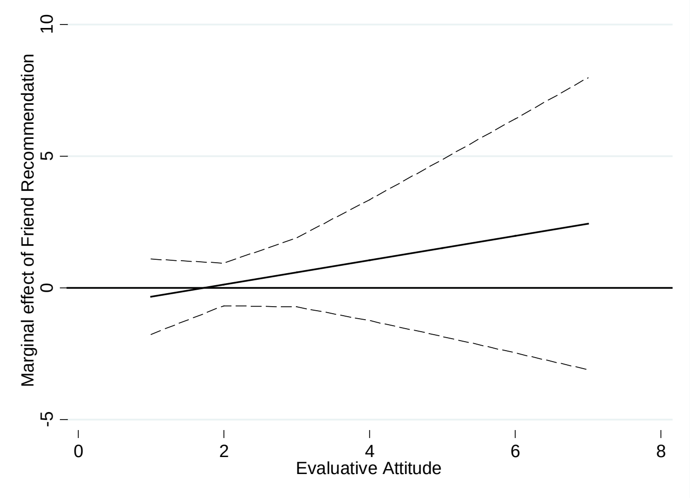
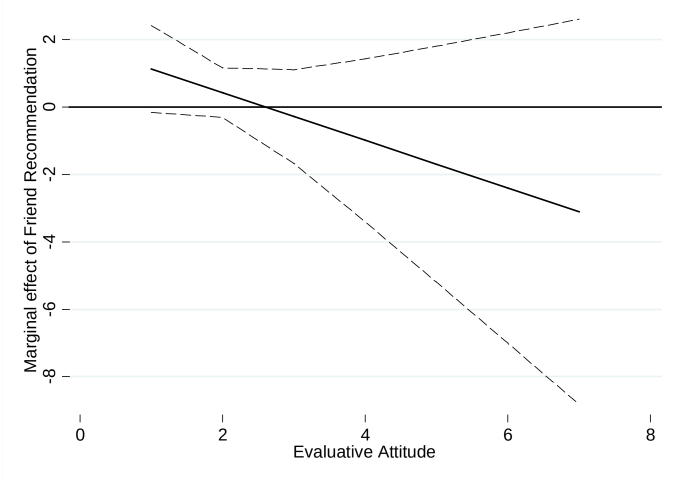
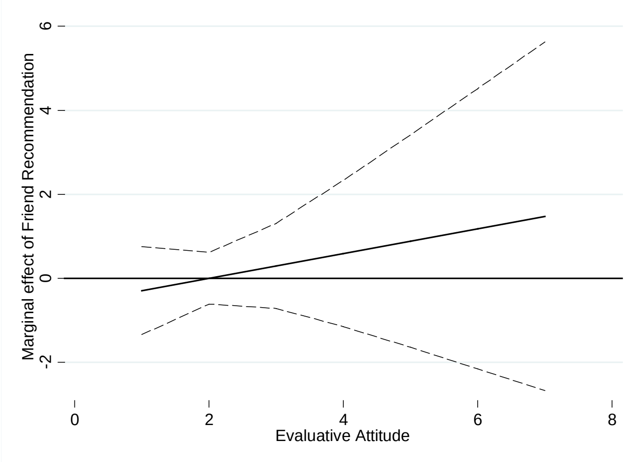
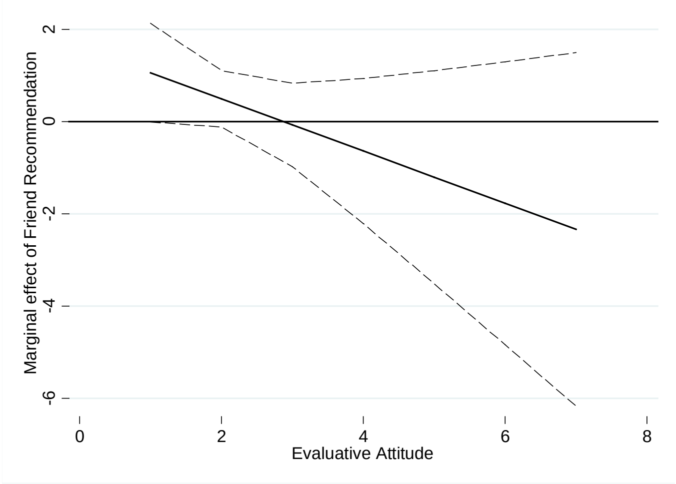
	Left-side Product	**Right-side Product**
Evenly Popular Pair		
Unevenly Popular Pair		

Table 3-7 The Marginal Effect of Friend Recommendation

	Left-side Product	Right-side Product
Evenly Popular Pair		
Unevenly Popular Pair		

3.6 Discussion

Prior studies in computer recommendations exclusively focus on the product discovery processes of utilitarian products. We broaden the scope of this literature by examining the role of computer recommendations in hedonic shopping contexts. In addition, we also deepen the understanding of underling mechanisms by examining the role consumers' evaluation attitude during the product evaluation process. The reason we do not find support for friend recommendation is probably related with alternative explanations for accepting a friend recommendation. For instance, one may be in favor of a friend recommendation to merely express support in public.

This experiment study can be improved in several ways. First, as shown in the result, popular products might be impacted by computer recommendation in a very different way from less popular products. More rigid study need to be carried out to investigate the moderating effect of product popularity. Chen et al. (2004) found that the marginal effect of a book recommendation appears to diminish with product popularity. Such argument may also holds for crowd endorsement in symbolic goods consumption.

Second, future study should randomly assign product s to either the right or left side, since when two products are with similar popularity, people tend to choose the first product (left one) when crowd recommendation is provided. Third, as we do not compare friend recommendation with crowd recommendation directly, future study can split the investigation to two separate studies, which will reduce the complexity in experiment design.

This lab experiment extends the understanding of social endorsements on both the aggregated and the atomic level, by going deep into consumer's value-expressive attitude in evaluating the symbolic goods. Our analysis indicates that evaluation support technologies, i.e., friend recommendation and crowd recommendation, does not always play a reinforcement role in affect one's attitude towards the products. A support artifact that is helpful to one group of consumers may prove worthless to others, or even hinder them.

Chapter 4. Conclusion

Social endorsements enable product discovery by exposing shoppers to their peers' collections, e.g., their favorites, reviews, and idea boards. However, social endorsements can also influence users' evaluation of products. In fact, for symbolic products such as fashion goods, social influence plays a dominant role in forming the preference among functionally equivalent alternatives. The evaluation function of social endorsement sets it apart from computer recommendations and allows it to flourish in areas where traditional e-commerce does not, such as fashion goods and interior design. With its increasing popularity across social media platforms, the investigation of social endorsements is bound to be fruitful. This is one of the first papers that embark on such investigation, by evaluating the disaggregated and aggregated value of social endorsements, in terms of consumers' private and public behaviors. After spot evidence from archival data in the first study, we extend the exploration to consumers' characteristics that influences the effect of disaggregated and aggregated social endorsements.

Appendix

Appendix A. Variables and Their Definition

Definition	Variable name	Description of variables
Dependent Variables		
Examination	$NewClicks_{it}$	Number of times a product is viewed from t-1 to t
Endorsement	$NewLikes_{it}$	Number of likes a product received from t-1 to t
	$NewSets_{it}$	Number of sets that a product is involved from t-1 to t
Explanatory Variables		
Product characteristics	$Discount_{it-1}$	Display Price/Original Price at time t-1
	$DisplayPrice_{it-1}$	Display Price at time t-1
	$OriginPrice_{it-1}$	Original Price at time t-1
	$AgebyMonth_{it}$	Time elapsed since a product first being introduced to the community (in month) at t
	$Soldout_{it-1}$	0: In inventory; 1: marked as sold out at time t-1;
	$ProductType_{i}$	0: Functional; 1: Symbolic;
Social influence	$NewLikerFollower_{it-1}$	Aggregated incoming network centrality of those who liked the product from t-2 to t-1
	$NewCreatorFollower_{it-1}$	Aggregated incoming network centrality of those who created one or more sets including the product from t-2 to t-1
Observational learning	$Likes_{it-1}$	Number of total previous likes a product received at t-1
	$Sets_{it-1}$	Number of previous sets that a product involved at t-1
Marketing exposure	$Promotion_{it}$	Number of days that the item being highlighted on homepage
	$PageRankSimilar_{it-1}$	A product's eigenvector centrality in the network of the computer-recommended similar items at time t-1
	$PageRankColike_{it-1}$	A product's eigenvector centrality in the network of the computer-recommended co-liked items at time t-1

Appendix B. Correlations among the main variables

		1	2	3	4	5	6	7	8	9	10	11	12
1	*Log(NewClicks$_{it}$)*	1.00											
2	*Log(NewLikes$_{it}$)*	0.51***	1.00										
3	*Log(NewSets$_{it}$)*	0.33***	0.53***	1.00									
4	*Log(Likes$_{it-1}$)*	0.48***	0.64***	0.44***	1.00								
5	*Log(Sets$_{it-1}$)*	0.35***	0.59***	0.51***	0.77***	1.00							
6	*Log(NewLikerFollower$_{it-1}$)*	0.48***	0.67***	0.42***	0.59***	0.51***	1.00						
7	*Log(NewCreatorFollower$_{it-1}$)*	0.31***	0.50***	0.49***	0.46***	0.55***	0.46***	1.00					
8	*Log(OriginPrice$_{it-1}$)*	0.16***	-0.01	-0.06***	0.07***	-0.12***	0.05***	-0.02*	1.00				
9	*Discount$_{it-1}$*	-0.05***	-0.02	-0.01	0.01	0.01	-0.01	-0.01	-0.02	1.00			
10	*AgebyMonth$_{it}$*	-0.05***	0.04***	0.02	0.22***	0.25***	-0.01	0.01	-0.25***	0.07***	1.00		
11	*PageRankColike$_{it-1}$*	0.19***	0.32***	0.20***	0.24***	0.27***	0.21***	0.19***	-0.29***	0.02*	0.13***	1.00	
12	*PageRankSimilar$_{it-1}$*	0.20***	0.21***	0.17***	0.20***	0.24***	0.17***	0.13***	-0.28***	0.03**	0.23***	0.22***	1.00
13	*Soldout$_{it-1}$*	-0.60***	-0.19***	-0.15***	-0.07***	-0.05***	-0.21***	-0.13***	0.03***	0.08***	0.08***	-0.14***	-0.20***

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

Appendix C. Posters Used in this Experiment

Product pair1		
Product pair2		
Product pair3		
Product pair4		
Product pair5		

Appendix D. Summary for Fifty Polyvore Member Interviews

1. Virtual life versus Real life (Self-Expression) Users create styles with pieces of cloth they like and would love to wear in real life, although some items are not affordable to them at present. At the same time, users reported that the style of the set depends on their current mood. Below are responses from different interviewees.
All my sets feature things I'd actually wear or would love to own in real life. *I get my style gene from my father. He's in the business of fashion and has taught me to make sure you always dress for your audience. I sometimes follow that rule, but I have to say, that I typically dress according to my mood.* *My set style depends on my mood. I always want to make sure it's wearable and something I would personally wear.* *I always recreate my own outfits with pieces that I would like to own, or I offer an affordable version of styling.* *Polyvore has been an artistic outlet for me at a time in my life when it's just not practical to buy.* *It has helped me refine my taste in clothes and develop a style that, while not necessarily unique, is my own.* *Obviously though, as a teenager, my resources are limited, so I don't wear any of these brands in real life.* *I think it's a great opportunity to express yourself and broaden your mind.* *Polyvore has become a daily thing for me. I can't even begin to express how it has changed my life. At first it was a hobby, but now it's become so much more. Because of Poly it has become so clear to me what I want to do as my profession.* *I am able to create my own personal sets and share them with the public.* *Polyvore has helped me develop my own style. I no longer wear whatever my friends are wearing or whatever I see people around me wearing. Instead, I now choose the things that I enjoy. I shop for things that fit my taste. I have a deeper understanding of my taste now, and I don't know if I would have found that had I not stuck with Polyvore.* *My sets don't have a particular style. They are pretty simple; I try to put the focus on the clothes, doing it according to my mood and what I want to transmit in that moment.* *It's changed how I look at clothing. I've been exposed to more brands, designers, and online shops. Whenever I save an item I feel like I've gone shopping. I have so many items clipped and saved and I love going through them and using them all.*

2. Social Interactions (Communication)

Users are in love with the ‘following’ button, so that they can keep track the newly created sets of their connections. Also, they are aware that other people are also following them, and wish to provide inspiration to their followers.

The first thing I like to do as soon as I sign in is check out the amazing new sets of all those I'm following. It's such a fun and inspirational way to start my day. I also love reading the feedback I get. It keeps me smiling. It always amazes me how sweet and supportive the Polyvore community really is.

These hoarded magazines have inspired my sense of style on Polyvore and I hope it gives my followers some inspiration on how to style their lives.

I start with creating a set of posts for the next day and I finish with checking my contacts' sets.

I remember helping someone in the "Ask" boards pick bridesmaid dresses for a wedding. She later messaged me and told me she was going to use the very dress I'd suggested! It was so fascinating to have a real, tangible impact. (Note by Pei: the Ask boards function has been closed by Polyvore, in order to have people concentrated on the style sets.But the old posts can still be browsed.)

I also love the Polyvore community which is very supportive and inspirational. Polyvore is part of my everyday life. I'm always signed on. I usually check my daily activities, messages and explore my friends’ sets and like them. I also like to check exciting new trends.

I have also made deep friendships with people around the world on this site, and have been able to connect with and be inspired by some truly remarkable people. I have met two of my Poly friends in real life and text, e-mail, and call one Poly friend regularly. I find the site to be a bit addicting and sometimes have to remind myself to go outside and play!

I love “meeting” people from all over the world who share a common interest in fashion.

I am able to create my own personal sets and share them with the public.

Polyvore has helped me make friends all over the world. I'm always signed in! Every time I turn on the computer, I check Polyvore. First thing I do is check my messages and talk to my friends. Then I browse through everyone's creations.

Polyvore has given me: (a) a greater love of fashion and interior design (b) new friends and (c) my own personal style. I also gained an array of friends from all over the world, which is just pretty awesome. Meeting new people from different cultures, countries and walks of life has been very eye-opening and amazing; definitely an experience that you cannot achieve on most websites.

I started using Polyvore four years ago. I don't remember how and or the exact day, but I've been in love with fashion ever since! Besides, I've made a lot of nice friends over here.

I sign on directly to my home page and look for the red number to check whether I need to respond to anyone. Next I go the top sets and do congratulations. Then I check the following-creations tab and look at the new sets of those I am following. Then finally I go to my drafts to see whether there is anything ready to publish or finish creating. Then I have to PULL myself away to get ready for the day!

I love the "Following" link because I get to see new creations instantly from the other amazing Polyvore members. I follow so many people, it is hard to keep track. So this feature helps a lot.

Having access to so many forms of fashion and art at the click of a few buttons is very gratifying and helps feed my need for creativity. Not only has it made boring days more fun, but I have also met some great, inspirational friends along the way. The first thing I do when I sign on is view my likes and comments, followed by some visual drooling over other people's sets.

3. Style Some users have a clear idea of what their styles are, while some think their styles are hard to capture.
My set style actually depends on what is going through my head at the moment I create them. So if I'm feeling a bit down and it's raining outside, I'm most likely indoors sitting on my computer, with a tub of ice cream, and pouring everything into a set. *My sets don't have a particular style. They are pretty simple; I try to put the focus on the clothes, doing it according to my mood and what I want to transmit in that moment.* *My set style is for sure colorful.* *I enjoy using bright and bold colors. I like to mix up classic styles with a trendy twist.* *A couple months ago my set style was kind of "crystallized," I guess. I started leaving white edges on everything to make the image seem cleaner (which can be a lot of work with custom borders, but worth it). I like an even balance of pictures and magazine articles. While it can be really time consuming, I try to find fashion editorials and random photographs with the same colors and aesthetic of the outfit I'm featuring. And then I throw on colored flowers and paint splotch effects to accent the whole image and fill negative space.* *I really don't care what people say about my style and my outfits, I wear what I love. I don't mind if it doesn't please others as long as it pleases me. If I feel good, that's all that matters.* *My personal style is hard to label, but my professors called it "whimsical," if that counts! Things like girly, floral prints, draped knits, grungy oversized tops and structured woven shorts can all be found in my closet. I add personality to each outfit with cutesy jewelry found on Etsy or eBay.* *Polyvore has helped me develop my own style. I no longer wear whatever my friends are wearing or whatever I see people around me wearing. Instead, I now choose the things that I enjoy. I shop for things that fit my taste. I have a deeper understanding of my taste now, and I don’t know if I would have found that had I not stuck with Polyvore.*

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