

Shopping as a Social Activity: Understanding People's Categorical Item Sharing Preferences on Social Networks

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ABSTRACT

Social commerce connects people's shopping activities with their social communities. Much work has leveraged social network data to promote sales of products and services. However, less is known about the impact of shopping activities on people's social relationships. This paper serves as foundational work in the field and addresses this gap by exploring people's preferences in sharing products and services on social networks, in order to gather knowledge for future design of personalized online shopping and social experience. Our study shows that "Electronics & Computers," "Home, Garden & Tools" and "Toys, Kids & Babies" are the most preferred product categories for people to share. Survey responses also identify that the factors of "Information" and "Sociality" highly impact what items people choose to share on social media. Additionally, this study explores the difference between participants' *intention* and *behavior* when sharing items on their social network. We compared the results from two groups of participants and detected noticeable differences between people's intent-to-share and actual sharing behavior in social commerce, generating interesting implications for researchers, businesses, and developers.

Author Keywords

Social Commerce; Social Network; Social Relationship; Personalization;

ACM Classification Keywords

Design; Human Factors; Management

INTRODUCTION

Social commerce is a rapidly developing area, promoted by the popularity and advancement of social networking sites (SNSs) [23]. Enabled by social networking technology, social commerce has emerged as a derivative of "e-commerce," where users communicate, write reviews and comments, rate products, and share the experience while shopping on the Internet [16]. Shopping in a social interactive environment enabled by social media systems provides a different experience compared with shopping in brick-and-mortar stores and on traditional retailers' websites [34]. The rapid growth of services using a

combination of social networking and e-commerce raises many research questions about the characteristics of social commerce, as well as opportunities to optimize people's experience by personalizing interfaces to combine online shopping activities and social relationships. Typically, social commerce is a form of Internet-based social media that allows people to actively participate in the marketing and selling of products and services in online marketplaces and communities [39], and involves properties like word-of-mouth, trusted advice, or buying with the help of friends [28]. Extending Mathwick's [29] online consumer behavior typology, social behavior and attributes in online shopping have been focused on relationship building that leads to new product discovery and the development of feelings of warmth and satisfaction through the online shopping process [37]. Despite the lack of standard definition for social commerce, the power of users' participation in online shopping activities has been widely recognized by many scholars in business management and information systems.

Researchers have discovered that social relationships and interactions of individuals influence consumer behavior [16]. However, there is a lack of current social commerce research about how online shopping activities and the personalization of shopping experience may have impacts on social relationships, and how the influence varies among different categories of shopping behaviors has not been widely studied. Though theoretical evidence for the fusion of social and commercial activities has been confirmed [26], only a few studies examine product categorical effects and differences in consumers' behavior and expectations in the context of online and social commerce. As foundational work of the under-studied area, one major objective of this paper is to identify the space for social relationships to emerge in the context of social shopping – the categories of products and services that people prefer to share and talk with others when shopping online – to inform interface design of social shopping apps that integrate personalized experience of shopping and social interactions in the future.

BACKGROUND AND RESEARCH QUESTIONS

Previous works have examined the combination of social networking and online shopping activities from various perspectives in order to understand people's behavior in social commerce environments, especially social interactions integrated in people's online shopping activities. For example, ratings and reviews have been

regarded as one of the key constructs that shape social commerce, as individuals could easily post their product reviews online and rate products, and therefore yield impacts on others' shopping intentions [8]. Social media websites, like Facebook and Instagram, no longer only serve as places for people to chat, share, and comment, but also as a platform that facilitate interactive activities to increase the level of trust and intention to buy products, which is generally referred as social commerce [16].

To understand how people's online interactions lead to impact on shopping intentions and behaviors, the relationship between trust and shopping intentions in an online context has been widely studied [13,21,31]. Existing research works discovered that customers' intention to purchase products online was not only influenced by trust in the web vendor [20], but, in the context of social commerce, also greatly impacted by three factors, "perceived ability, perceived benevolence/integrity, and perceived critical mass" on trust in product referrals from social network contacts [17]. Additionally, prior investigations of the social aspect of social commerce proposed to understand the adoption of social shopping websites by examining social factors such as social comparison, social presence, and enjoyment, based on the Technology Acceptance Model [12] theoretical framework [37]. A good understanding of the relationship between shopping intentions and online social interactions is key to personalized interface design of effective social shopping apps [21].

Product Categorical Effects

We believe items that people shop online are quite different, in terms of how likely people would like to socialize with other people on social media (i.e. share, comment, and discuss). To explore the under-studied area of social commerce on social relationships, this paper is to identify the product and service categories that people prefer to share on social networks in online shopping activities. One limitation in most of the research discussed above is the over-conceptualization of shopping in online contexts, which considered online shopping in general without identifying the differences in the nature of a wide variety of items.

Early research in e-commerce studied people's categorical preferences of shopping in online and offline channels, and the results indicated that people do prefer to purchase certain categories of items online, and certain categories offline. For example, Levin et al. [22] addressed the question of how to combine online and offline services in the most complementary way for different product categories, based on the results from two experiments and a series of surveys. As summarized in their research paper [22], for products like clothing, consumers place great value on the ability to touch and inspect the product and therefore they prefer offline, bricks-and-mortar services, while for products like electronics, consumers place great value on

the rapid dissemination of large amounts of information through Internet search.

Despite the rich literature in social networking and online shopping, such product category differences were underdeveloped in the context of social commerce. Little has been discovered about the product category-dependent consumers' preferences for traditional online shopping and social commerce. In this paper, as the first step to gain knowledge for personalization of people's social shopping experience, we aim to address the product categorical effects in social commerce, and identify the most complementary way to combine traditional Business to Consumer (B2C) e-commerce and social shopping activities by exploring research questions from both the social commerce and the traditional online shopping perspectives.

Social Commerce on Social Relationship

Another limitation of the previous work in social commerce is the lack of examination on the relationship and influence between social relationships and social commerce. Many scholars have investigated the impact of social networking on people's shopping behavior, but limited works have examined the other direction – how social commerce behaviors impact people's social relationships. Byrne [7] proposed Similarity-Attraction Effect in his paper, which referred to the widespread tendency of people to be attracted to others who are similar to themselves in important respects. A good number of previous works indicate that when users share similarities in demographics, interests, and attitudes, they become more attracted to each other [30]. These attributes were mostly identified in the personal information of users' profiles [19]. We believe social relationships may establish, maintain, and improve their social relationships in the socialization process of online shopping activities. In many cases of social commerce, users may discover the similarities in interests and/or attitudes with their friends on social networks during the interactive shopping processes. In this paper, we focus on exploring what factors may affect users' decisions of sharing items on social networks with their family and friends, so as to examine the impacts of social commerce on interpersonal relationships.

Intention vs. Behavior

According to Liang and Turban [23], *empirical surveys, experimental studies, longitudinal studies, case studies, conceptual development* and *technology design* have been the major methods used in social commerce research. Among these methodologies, *surveys (35%)* and *experimental studies (20%)* are the most widely used research methods in related works [3].

Traditionally, researchers have used survey questionnaires to study people's perceptions, attitudes, and intentions [35]. For example, Levin et al. [22] conducted a series of surveys to study people's intentions in the context of online and offline shopping, so as to determine consumers' preferences

for different categories of products. However, users' intentions were not always translated into action, which is typically referred to as the "intention-behavior gap," reflecting the black-box nature of the underlying psychological process that leads from intention to action [39]. As a foundational work in this exploratory area, we would like to make sure "people do what they say".

To study the preference of product categories in the context of social commerce, we used two conditions to examine people's intentions and actions. In Condition 1, we used a survey questionnaire to measure people's intention of what categories of products they would consider posting (i.e., intend) on their social network, and in Condition 2, we asked people to actually post the products of their choices on Facebook to share with their family and friends. We analyzed the results of the two conditions to compare people's intentions and actual behaviors, and also to measure the intention-behavior gap on people's preferences of what categories of products to share on social networks.

Research Questions

To provide deeper insights into the product categorical preferences of people sharing items with others in online shopping, we conducted an empirical study to help the researchers and businesses to accumulate knowledge concerning this under-studied area for future exploration and development. In addition, the paper also aims to study the underlying factors of people's sharing decisions by analyzing the survey responses from the participants. Moreover, we also examine whether the intention-behavior gap exists when people choose what categories of items to share on social networks, which might be useful for researchers to decide the methodologies to use in future works in the field. Therefore, the paper addresses the following research questions (RQ):

RQ1: Do people have preferences of what categories of products to share with their family and friends on social networks?

RQ2: What factors do people consider when deciding what categories of items to share on social networks?

RQ3: Does intention-behavior gap exist in people's preferences in choosing what categories of items to share on social networks?

METHODOLOGY

Task

This study has three major objectives for understanding people's categorical preference in the context of social commerce: 1) to identify the categories of items people prefer to share with their family and friends on a popular social network; 2) to understand the factors that lead to the preferences; and 3) to determine whether "intention-behavior gap" exists in people's sharing of shopping activities on social networks. We examined these three objectives through the use of a two-condition study.

Part	Condition 1: <i>Intention</i>	Condition 2: <i>Behavior</i>
Background Information	Social network and online shopping experience	
Item Sharing Task	1. Pick 2 to 5 items from Amazon.com 2. List the links to the items on the survey	1. Pick 2 to 5 items from Amazon.com 2. Share the items on Facebook timeline 3. Take a screenshot and upload
Factors for Posting	Rating of considering "factors" when deciding which items to share on Facebook	
Reward	\$0.10 per person	\$0.30 per person

Table 1. Experimental design of two conditions in the task.

We developed an online survey on SurveyMonkey,¹ and conducted studies with two different conditions – the first measuring *intention* and the second examining actual actions of people's item sharing on Facebook. Each of the tasks consisted of three parts in the survey questionnaire:

1) social network and online shopping background; 2) item sharing task; and 3) factors for posting.

All of the survey questions were identical in both *intention* and *behavior* conditions, with only the assigned item sharing task differing between the two conditions.

For the *intention* group, the first part of the survey consisted of participants answering questions about how long and how frequently they have shopped online, and how many Facebook friends they have in total. Next, in the second part of the survey, the participants had to choose 2 to 5 items from Amazon.com that they would share with their family and friends on Facebook, and provide the links to the items in the questionnaire. They did not have to actually post these items on their Facebook timeline. Finally, after completing the item sharing task, in the third part of the survey, the participants had to rate different factors that may have impacted their item selections, such as privacy concerns, information seeking, and common interests among Facebook friends.

The *behavior* group followed the same overall structure of the design as the *intention* group. However, for the second part of the survey, instead of listing the links of items in the survey as the *intention* group did, the participants of the

¹ SurveyMonkey: <http://www.surveymonkey.com>

behavior group had to actually post links of their selected items on their Facebook timeline, and upload screenshots of their item postings via a Dropbox² link accessible to the researchers. Like the *intention* group, in the third part of the survey, the *behavior* group participants then rated the factors that impacted their choices of items shared on Facebook. As shown in Table 1, the objective of the experimental design of our tasks was to set up two separate tasks for the participants, while keeping as many parts identical as possible in the study.

Participants and Recruitment

Social commerce refers to the use of social media for commercial activities that are driven primarily by social interactions and user contributions [33]. We targeted people that are both Facebook users and online shoppers, defined

	Characteristics	<i>Intention</i> (n=113)	<i>Behavior</i> (n=98)
Gender	Male	32.7%	39.8%
	Female	67.6%	60.2%
Age	18-24	13.3%	14.3%
	25-34	49.2%	59.2%
	35-44	23.9%	14.3%
	45 or older	13.3%	12.2%
Ethnicity	Hispanic	9.7%	10.2%
	White	61.1%	68.4%
	Black	14.2%	12.2%
	Asian	11.5%	5.1%
	American Indian	2.7%	4.1%
	Other	0.9%	0.0%
Education	High school or lower	20.4%	11.2%
	Bachelor	69.0%	76.6%
	Advanced degree	10.6%	12.2%
Online Shopping History	More than two years	85.8%	74.5%
	Two years or fewer	14.5%	25.5%
Online Shopping Frequency	Once every week	29.2%	32.7%
	Once every month	38.9%	37.8%
	Once every 3 months	22.1%	16.3%
	Less than once every 3 months	10.7%	13.3%
Number of Facebook Friends	100 or fewer	27.4%	30.6%
	101-200	18.6%	22.4%
	201-300	17.7%	12.2%
	301 or more	36.5%	34.7%

Table 2. Participants' demographic and background information.

as individuals who self-reported that they had made purchases online within the past two years. We used Amazon Mechanical Turk (MTurk) – an online marketplace where individuals can get paid for completing small Human Intelligence Tasks (HITs) – to recruit our participants.

We set our compensation to be high enough to attract participants, but also as low as possible to minimize participants' sense of obligation to complete our HIT. The participants in both the *intention* and the *behavior* groups were allowed to quit at any time after starting their tasks. To determine a fair market compensation rate for our HITs, we surveyed and participated in others' existing tasks on MTurk for one week, focusing particularly on tasks that required similar time and effort.

For the *intention* group, we set our compensation rate as \$0.10 per person. As mentioned in the previous section, each participant was asked to pick 2 to 5 items from Amazon.com that they would share (but not actually post) on their Facebook timeline with their family and friends, and provide the links to these items in the online survey. A total of 113 people participated in the *intention* group, providing a total of 352 valid item links.

For the *behavior* group, we tried to keep the compensation at 0.10 initially, but failed to attract enough participants at this level, as additional effort is required to finish the task.

We raised our compensation to \$0.30 per person for the additional effort required to actually post items/links on their Facebook timeline and provide us with screenshots. We offered this HIT after completing our data collection for the *intention* group to minimize the chance of the same MTurk worker from participating in both of our conditions. To ensure that we did not include past *intention* group participants in our analyses of *behavior* group participants, we asked the *behavior* group participants to prepend their unique MTurk worker identification number to their screenshot filenames, so we could exclude repeat participants.

In total, 98 *behavior* group participants generated 202 valid item postings on their respective Facebook timelines. Most participants used Amazon's "share" function to post the items directly from Amazon to Facebook, while some participants copied and pasted the links to share on Facebook timelines, both of which were accepted in our study. Figure 1 shows examples of screenshots from the participants in the *intention* group.

We collected data over several months during different times of the week and day. Also, our demographic data in Table 2 suggests that our group was skewed towards educated, white females, which was consistent with others'

² Dropbox is a cloud-based file storage site: <http://www.dropbox.com>



Figure 1. Screenshots of Facebook postings uploaded by a participant in the *behavior* group.

observations in MTurk recruitment [36]. Table 2 shows the demographics, social connections, and online shopping background information of the participants for each of the two conditions in our HIT.

RESULTS

Categories of Items Sharing on Social Network

As mentioned in the previous section, we asked the participants to choose 2 to 5 items that they would share on social networks from Amazon.com, the most popular shopping website in the U.S. [10]. Based on the responses, we then classified their selection of items by using the existing first-tier categories that each item belongs to on Amazon.com. However, some of the Amazon-brand product lines are listed as independent categories on the Amazon website, such as Fire TV and Echo & Alexa. These categories were adjusted based on the nature of the items. For example, if the participants picked Amazon Fire TV, Fire Tablet or Echo Dot in our HIT, the item was categorized under “Electronics & Computers” for further analysis.

We recorded the 352 item links provided by the participants in the *intention* group. Table 3 presents the product categories of items that the participants indicated they would share on their social network accounts. “Electronics & Computers” (92), “Home, Garden & Tools” (62), and “Beauty, Health & Grocery” (52) were the top three among the major product categories, accounting for half of the total item selections, followed by “Clothing, Shoes, & Jewelry”

Category	Count
Electronics & Computers	92
Home, Garden & Tools	62
Beauty, Health & Grocery	52
Clothing, Shoes & Jewelry	37
Movies, Music & Games	34
Toys, Kids & Baby	29
Books & Audible	19
Sports & Outdoors	14
Handmade	10
Gift Cards	3
Total	352

Table 3. Results of item sharing tasks by the *intention* group (n=113).

Category	Count
Electronics & Computers	49
Home, Garden & Tools	36
Toys, Kids & Baby	26
Movies, Music & Games	25
Clothing, Shoes & Jewelry	22
Beauty, Health & Grocery	13
Books & Audible	12
Sports & Outdoors	10
Handmade	5
Automotive & Industrial	4
Total	202

Table 4. Results of item sharing tasks by the *behavior* group (n=98).

(37), “Movies, Music & Games” (34), and “Toy, Kids & Baby” (29).

We recorded the 202 screenshot uploads provided by the participants in the *behavior* group. Table 4 presents the product categories of items that the participants actually shared on their Facebook timelines with their family and friends. The results of our study showed “Electronics & Computers” (49), “Home, Garden & Tools” (36), and “Toy, Kids & Baby” (26) were the top three among the product categories for the *behavior* group, with “Movies, Music & Games” (25), “Clothing, Shoes, & Jewelry” (22) and “Beauty, Health & Grocery” (13) ranked from the fourth to the sixth.

Factors of Item Sharing on Social Network

To understand how our participants made their item selection choices to share on Facebook with their family and friends, we used semantic differential for several items as shown below. We examined the responses using the twelve label items (see Table 5), including details of items, privacy concerns, general feedback, common interests and discussions, in the online survey. After indicating the items to share on Facebook, participants rated their agreement to the twelve statements listed in Table 5 on a scale from: 1 (Strongly Disagree) to 7 (Strongly Agree). The frequencies of the responses are as shown in Table 6, below.

Label	Measurement
	<i>“Please rate how you agree/disagree with the following statements: I posted the specific items that I chose on my Facebook page, because ...”</i>
<i>Detail</i>	... I’d like to know more details about the items from my friends (e.g. material, function, and durability).
<i>Privacy</i>	... I considered privacy an important factor when deciding which items to post.
<i>Appropriate</i>	... I considered the items as socially appropriate.
<i>Feedback</i>	... I’d like to get feedback from my friends about the shopping experience with the item (e.g. shipping, return policy, and customer support).
<i>Interest</i>	... some of my friends might be interested in the items I was sharing.
<i>Common</i>	... the items could elicit common interests.
<i>Price</i>	... I’d like to get feedback about the price I should pay for the item(s).
<i>General</i>	... I would like more general information about the item(s)
<i>Comfort</i>	... I felt comfortable letting my friends know the items I was interested in.
<i>Discuss</i>	... the posting may encourage discussion among my friends.
<i>Similar</i>	... my friends have shared/posted similar items.
<i>Concern</i>	... I had no privacy concerns for the items I was shared.

Table 5. Label items and the measurements in the HIT.

Ratings of the label items for considering products to share on social network

	1	2	3	4	5	6	7
Detail	5.2%	9.5%	10.0%	13.7%	21.3%	24.6%	15.6%
Privacy	5.2%	9.5%	11.8%	12.8%	16.1%	20.4%	24.2%
Appropriate	1.9%	2.8%	4.3%	7.1%	14.2%	32.7%	37.0%
Feedback	7.1%	6.2%	8.5%	11.4%	19.9%	27.0%	19.9%
Interest	2.4%	2.8%	4.3%	8.5%	17.1%	33.6%	31.3%
Common	3.3%	1.4%	6.6%	9.5%	19.9%	32.2%	27.0%
Price	9.0%	9.0%	8.1%	10.9%	17.1%	23.7%	22.3%
General	8.5%	5.2%	10.0%	17.1%	18.5%	22.7%	18.0%
Comfort	4.3%	3.3%	4.3%	4.3%	16.6%	32.7%	34.6%
Discuss	2.4%	3.8%	7.1%	10.4%	17.1%	32.7%	26.5%
Similar	5.7%	10.0%	10.0%	13.3%	13.7%	25.6%	21.8%
Concern	5.7%	6.6%	5.7%	14.7%	14.7%	24.6%	28.0%

1: Strongly Disagree; 2: Disagree; 3: Slightly Disagree; 4: Neither Agree nor Disagree; 5: Slightly Agree; 6: Agree; 7: Strongly Agree

Table 6. Frequencies (%) of label items constructing the research variables (N=211).

Since the measuring scale used in this study was not from prior work, we performed factor analysis [43] to uncover underlying factors (constructs) for the twelve label items (in Table 5). We ran the Factor analysis (Principal Axis Factoring) with Oblimin rotation on the responses to the twelve label items. As suggested by Moss [32], a low communality (<0.4) suggests that an item is not adequately explained by any of the factors. We performed the factor

analysis iteratively and removed label items as needed, based upon communalities being too small and/or evidence in the Structure Matrix of cross loading. For example, we removed the “privacy” label item during the first iteration of factor reduction analysis, as the communality was 0.29 (<0.4). We then performed the second iteration with the remaining items, and removed label items, “similar” and “concern”, as needed in subsequent iterations. The iterative process continued until all label items returned satisfactory communalities and factor loading values, for a total of three iterations. We also examined the residuals each time to ensure whether another factor should be included. After a series of Factor Analysis iterations, we found a two-factor solution, with adequate communalities and no cross loadings, for nine of the label items as shown below in Table 7, where bolded values indicate the classification of the label items into variables of interest. Based on the results, we consolidated the factors into two new variables that we labeled as: *Information* (\bar{X} =4.79, sd =1.55) and *Sociality* (\bar{X} =5.57, sd = 1.26).

	Information	Sociality
Detail	0.798	0.390
Feedback	0.741	0.372
Price	0.824	0.348
General	0.811	0.346
Appropriate	0.321	0.707
Interest	0.345	0.877
Common	0.307	0.789
Comfort	0.413	0.854
Discuss	0.480	0.770

Table 7. Results of Factor Loadings

	Information	Sociality	OSH*
Information	1.0	r=.42, p<.01	r=.04
Sociality		1.0	r=-.16, p<.05
OSH*			1.0

*OSH = Online Shopping History

Table 8. Correlations of data for variables of interest

We used a paired t-test to compare the two variables of interest: Information and Sociality. There was a significant difference in the values for “Information” (\bar{X} =4.79, sd =1.55) and “Sociality” (\bar{X} =5.57, sd = 1.26); $t(210)=-7.407$, $p<0.001$. The results showed the participants considered significantly higher impacts of “Sociality” than “Information” for products to share on social network. This suggests, compared with seeking “Information” from their Facebook friends, the participants considered “Sociality” of the products (e.g. common interests, discussion among friends) as a higher priority factor in deciding what items to share on social networks.

We used non-parametric statistical tests for our analyses because a Kolmogorov-Smirnov one-sample test on our data revealed that it was not normally distributed. Then we performed nonparametric bivariate correlation tests for Information, Sociality, and the background variables listed in the methodology section. The level at which the participants perceived “Information” and “Sociality” was not significantly correlated with any of the demographics variables (age, gender, or race). With regard to the online shopping background, we found, interestingly, “Sociality” did have significant negative correlations with “Online Shopping History” as shown in Table 8, which suggests that participants with shorter online shopping history considered more of “Sociality” of the products when sharing the items on social networks with their family and friends. However, no statistically significant relationships were discovered between the variables of interests (“Information” and “Sociality”) and “Number of Facebook friends” or “Online Shopping Frequency.”

Product Category Comparison of the Two Groups

To address the intention-behavior gap [39], we compared the items that participants in each of the two groups chose to share on social network. In our HIT, participants in the *intention* group provided us with the links to the products, while those in the behavior group were asked to post the items on their Facebook timelines and upload the screenshots of their postings as proof of their task completion. Table 9 presents the combined category counts of the items that our participants chose to share in the HIT.

As shown in Table 9, the top six categories were consistent across the two groups of participants, but with a different ranking order in some of the popular product categories. For example, “Electronics & Computers” were the favorite categories for participants in both groups, while “Beauty, Health & Grocery” dropped from 3rd place for the *intention* group to 6th place for the *behavior* group. Moreover, we noticed “Toys, Kids & Baby” came 3rd in ranking for the

behavior group with a much higher percentage than that by the *intention* group.

DISCUSSION & DESIGN IMPLICATIONS

Our findings demonstrate people’s categorical preferences of sharing items on social networks with family and friends. By examining the results of the survey responses, we also identified the factors of postings, “Information” and “Sociality”, which have an impact on people’s choices of items to share on Facebook. In this study, the comparison of the results from the *intention* group and the *behavior* group also generated some interesting implications for business managers and social commerce researchers. The results have several design implications for future personalized social shopping apps, including the emphasis of categories that engage users’ shopping experience in social interactions, social attributes of certain items in social shopping contexts, and appropriate methodology that approaches the area of online shopping as a type of socialized activities.

Categorical Preferences of Social Commerce

Categorical preference indicates consumers’ behaviors and likelihood of satisfaction toward different types of products [11]. The results of the study described in this paper show that people do have categorical preferences of sharing certain products on social networks. For example, “Electronics & Computers” items were the most widely shared by the participants in our HIT across both conditions, followed by “Home, Garden & Tools,” “Beauty, Health & Grocery,” “Clothing, Shoes, & Jewelry,” “Movies, Music & Games,” and “Toy, Kids & Baby,” among the popular categories for people to share on Facebook. Our findings are consistent with previous research on consumer preferences of online and offline shopping methods [22]. The preference patterns emerged as people become more reliant on online shopping channels, and shopping activities evolving into social behaviors as a phenomenon of global interest for marketers, businesses, and researchers [3]. To inform future research, this paper identified the preferable categories of products that may facilitate “bridging” channels between shopping activities and social relationships. For example, to develop personalized social shopping apps for the users, researchers and designers may bootstrap or start their process by focusing first on the top categories that people have the most intents and willingness to share and discuss among online social communities, instead of building apps or systems that cover all categories of products and services.

Information Seeking and Perceived “Sociality”

Recent developments of social commerce enables social media users to easily share product information, seek advice from their social community about their purchasing decisions [24], and articulate attitudes toward products and services [25]. The findings of this paper also confirmed that people consider information and advice-seeking as important factors when sharing products on social networks. The data from our survey suggested that one

Category	Intention (n=352)	Behavior (n=202)	Ranking Diff.
Electronics & Computers	26.1%	24.3%	0
Home, Garden & Tools	17.6%	17.8%	0
Beauty, Health & Grocery	14.7%	6.4%	-3
Clothing, Shoes & Jewelry	10.5%	10.9%	-1
Movies, Music & Games	9.7%	12.4%	+1
Toys, Kids & Baby	8.2%	12.9%	+3
Books & Audible	5.4%	5.9%	0
Sports & Outdoors	4.0%	5.0%	0
Handmade	2.8%	2.5%	0
Gift Cards	0.9%	0.0%	-1
Automotive & Industrial	0.0%	2.0%	+1

Table 9. Results of item sharing tasks for each category.

major driver of people sharing items on social networks is the feedback from their social friends, including price, functionality, product details, and customer experience. In addition, we found that perceived “sociality” of products also plays an important role for people to consider sharing items with their family and friends. This study found that people prefer to share items that may provoke common interests among friends and trigger discussions on social networks. It might not be surprising to identify a correlation between “sociality” of products and people’s sharing preferences. However, this paper contributes a new dimensional attribute of product to consider for future research to understand people’s behaviors, attitudes, and preferences in social commerce and social relationships. For researchers and developers, the focus of designing such social apps and systems should be building an online community that engages people in discussions and interactions, rather than an online shopping Question-and-Answer platform. Also, it would be very interesting to explore an algorithm calculates relative social attributes of a variety of items, and how the social attributes of the items may be related to individual users, which leads to the automation and personalization process of “item sharing” suggestions and matching of “shopping friends” (i.e. Amazon friends, eBay friends).

Comparison of Intention and Behavior

One objective of this paper was to examine the “intention-behavior gap” in the context of categorical preferences in social commerce. To address this question, we compared the results from two separate groups, an *intention* group and a *behavior* group. The data shows that the two groups of participants shared the top six categories of items in our HIT, but not necessary in the same order, with “Electronics & Computers” being the most popular category to be posted on social networks.

Though these results do not indicate a strong “intention-behavior gap”, it is still interesting to notice and analyze the differences in the ranking order of some popular categories of items between the two groups of participants, as shown in Figure 2. For example, a much higher percentage of

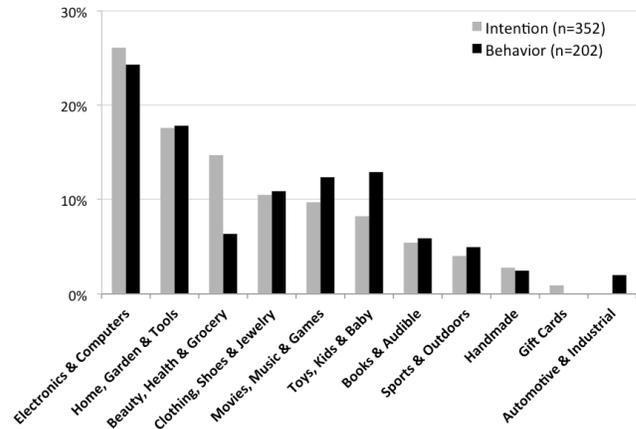


Figure 2. Summary of study results for the two groups of participants (% adjusted)

participants in the *behavior* group preferred children-related products to actually be posted on their Facebook timelines.

There are several possible interpretations of the results in our HIT. The higher rank of “Toy, Kids & Baby” in the behavior group might be because “sociality” played a more important role when the participants were asked to actually post the items of their choice on Facebook. In comparison, the participants in the *intention* group were just required to provide the links to the items instead of posting them on social networks. Therefore, it is possible that the participants of the *intention* group were confused with the differences between “what to buy” and “what to share” in this context, while the *behavior* group more clearly focused on the “sharing” – social attributes of the items that they chose to share with their family and friends.

LIMITATIONS

We recognize that our study has several limitations that may pose threats to the generalizability of the results in this paper. First, MTurk allows participants to self-select into HITs, and our HIT only required that participants were residing in the U.S. Also, MTurk workers are considered tech-savvy, as they need to complete tasks on online platforms [36]. The sampling bias may also limit the generalizability of our results to a more general public.

Second, the categories of items that Amazon.com carries as a retail website are also limited. For example, our participants were not able to choose certain items, such as cars, hotels, and travel packages, to share on social networks in our HIT. Some of these categories may also have high “sociality” attributes that may serve as good fits for people to share and discuss with their family and friends, to establish, maintain, and improve their social relationships.

Third, there was an economic incentive for participants to participate in our HIT. Though we tried to minimize this effect as much as possible, it might still be possible that

MTurk workers just completed the task for the monetary gain without thinking seriously about the task, especially for the participants in the *intention* group, as they did not have to actually post on their social networks. Also, the participants were “asked” to share items on social media in an experimental environment, and we recognize that some participants may share items in our HIT, which they would not voluntarily share in their daily activities.

CONCLUSION & FUTURE WORK

This paper explored people’s categorical preferences of items to share on social networks. By comparing the results from the *intention* group and the *behavior* group, we found slight differences between people’s intentions and actual behaviors in sharing items with their family and friends on Facebook. As foundational work of the under-studied area and the first step in the process of automation and personalization of people’s social shopping experience, this paper identified the preferable categories of products that may “bridge” between shopping activities and social relationships. For example, to design an effective personalized interface of integrating online shopping in social interactions, researchers may start their work by designing apps or platforms with prioritized focuses on the top categories that people have the strongest willingness to share and discuss, instead of building social shopping apps or systems that cover all categories. From the results of the study, this paper also discovered that people consider “sociality” of the items more than “information seeking” when deciding what to share on Facebook. The results suggested that those “sociality” factors, such as common interests and discussions among social community, have greater impact on people’s preferences of sharing items on social networks, than seeking information and purchasing advice from their friends.

These findings raise many questions for future research work. For example, one possible direction could be extending the concept of “sociality” and research on how to better use algorithm to measure the social attributes of certain categories and items that bridge the gap between shopping activities and social relationships. For future works, researchers may focus on what items can lead to more interactions between friends in social communities, and have positive or negative impact on people’s social relationships. In addition, this paper identified the most popular categories of items that people prefer to share with their social communities. With the rising interest in research on shopping as a social behavior, we believe that more knowledge about the preferences of sharing shopping activities on social networks will be essential to our understanding of the impact of shopping behaviors on people’s social relationships and communities, as well as personalization of people’s shopping and social experience.

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