Mining Consumer Impulsivity from Offline and Online Behavior

Fuzheng Zhang†, Nicholas Jing Yuan†, Kai Zheng*,
Defu Lian‡, Xing Xie†, Yong Rui†
†Microsoft Research
*School of Information Technology & Electrical Engineering, University of Queensland
‡Big Data Research Center, University of Electronic Science and Technology of China
{fuzzhang,nicholas.yuan,xingx,yongrui}@microsoft.com,
kevinz@itee.uq.edu.au, dove.ustc@gmail.com

ABSTRACT
Consumer impulsivity is a psychological feature characterizing the impulsive buying tendency. In this paper, by bridging consumer behavior with perceived stimuli on social networks, we present a computational framework, termed Consumer Impulsivity Model (**CIM**), for exploring a consumer's impulsivity in both offline and online context: consumption-related location visit indicating consumption patterns in the physical realm, and online shopping behavior indicating economic activities on the Internet. To demonstrate the effectiveness of **CIM**, we conduct extensive experiments, with a large dataset we have collected from thousands of consumers. The results show that 1) for 103 subjects, the inferred consumer impulsivity has a positive Pearson correlation with survey results in the situation of product and product category, respectively. 2) females inferred impulsivity is higher than males on average in the situation of product and product category, respectively. Age has a negative Pearson correlation with inferred impulsivity in the situation of POI, POI category and product category, respectively. 3) for next behavior prediction, our model defeats several presented baselines. These results suggest that our framework CIM offers a powerful paradigm for 1) presenting an effective measurement for consumer impulsivity. 2) uncovering the correlation between consumer impulsivity and demographic factors and 3) revealing that the introduction of impulsivity is effective in predicting consumer behavior.

Author Keywords
Consumer Impulsivity, Check-in, Online Shopping

ACM Classification Keywords
H.2.8 Database Applications: Data Mining; J.4 Social and Behavioral Sciences: Psychology

INTRODUCTION

UbiComp'15, September 7-11, 2015, Osaka, Japan.

http://dx.doi.org/10.1145/2750858.2805828

Consumer impulsivity (one attribute contained in term of general impulsivity) has been described as a psychological characteristic measured in an individual making a consumption decision. This characteristic is a measure of an individual's tendency to act on a whim, and is behavior characterized by limited forethought, reflection, and consideration of the consequences [29].

Consumer impulsivity has been regarded as a ubiquitous and distinctive aspect of human lifestyles. It is reported that more than 70% of all the supermarket-buying decisions are unplanned or impulse purchases [18]. In a general sense, consumer impulsive behavior has been a target of philosophical discussion for many years [1]. Given the importance, considerable efforts have been invested in many scientific disciplines as varied as economics [8], psychology [21], and neurobiology [10]. In consumer behavior and recommender system research, understanding this personal characteristic is particularly crucial since consumers' attributes are strong indicators of their purchasing patterns [28].

Over decades, researchers have developed numerous scales to measure consumer impulsivity. For example, Puri and Radhika [23] presented Consumer Impulsiveness Scale and found that impulsive behavior is influenced by the relative accessibility of inputs such as the costs and the benefits of impulsiveness. However, similar to other this kind of survey or interview-based approaches, their work still replies on retrospective self-reports and thus is vulnerable to memory. In addition, the time and money cost, as well as the data granularity, limit the effectiveness and efficiency of these approaches for understanding consumer's impulsivity at a large scale.

In this paper, the question of interest is that can we understand consumer impulsivity computationally, especially from the perceived stimuli on social networks? During the past few years, the proliferation of social networking sites (e.g., Twitter, Facebook in U.S. and Sina Weibo in China) have facilitated connections between people based on shared interests, values, and memberships. On the one hand, the online word-of-mouth communication through social influence can provide incentives for impulse purchasing, since the suggestions from people they know and trust are usually strong stimuli [27]. On the other hand, the growth of online shopping and social media is fueling the demand of social commerce.

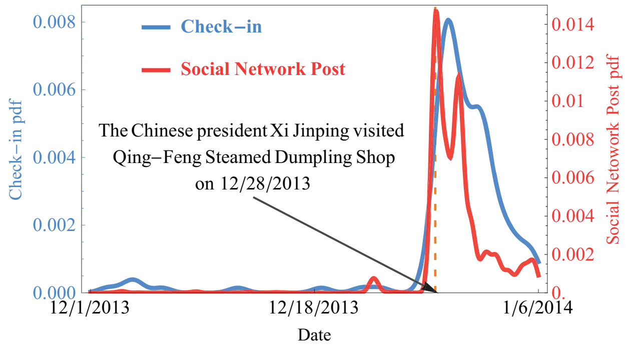


Figure 1. Qing-Feng Steamed Dumpling Shop-related check-in density distribution w.r.t Qing-Feng Steamed Dumpling Shop-related social network post density distribution

Thus, an increasing number of enterprises are devising new marketing strategies to increase online sales volumes by using these social network sites. Furthermore, Sina Weibo (the largest social network in China) and Taobao (the largest e-commerce website in China) announced a strategic alliance to cooperate in important areas including accounts-linking, data exchange, and internet marketing. The connection of social network activity and consumer behavior provides unprecedented potential for us to uncover consumer impulsivity implied by our everyday lives. Thus, by connecting visible posts on social networks with consumer's offline/online behavior, we can explore consumer impulsivity in a completely data-driven way. For example, Figure 1 shows after the Chinese president visited a given shop, there was a surge in both social network exposure of this shop and check-in frequency at this shop. The strong association between social network exposure and check-in frequency implies some consumers are impulsive triggered by stimuli from social networks.

In this paper, we first propose a data-driven framework called Consumer Impulsivity Model (**CIM**) to understand consumer impulsivity, triggered by stimuli from social networks. This model is flexible enough to characterize consumer impulsivity in both offline and online context. Next, we delve into the exploration of domain-specific impulsivity in check-in behavior, which reflects offline consumption patterns in the physical world, and online shopping behavior, which reflects economic activities on the Internet. Our evaluation consists of multiple parts. First, we conducted several experiments to validate our results by comparing them with a survey-based method, analyzing the distribution of impulsivity in various situations, and uncovering the relationship between impulsivity and demographic attributes. Next, we also compared the prediction results of our method with some widely adopted baselines to test the prediction performance.

Our work focuses on investigating and modeling consumer impulsivity from behavioral data. The main contributions of this paper include the following:

- We have developed a Bayesian approach to model consumer impulsivity by leveraging behavioral data and perceived stimuli on social networks.
- We offer in-depth analytics in exploring consumer impulsivity in both offline and online domains. The domain-specific activities reveal how impulsive behavior manifests itself in different aspects of consumer behavior.
- We conducted extensive experiments on a large-scale dataset to validate the effectiveness of our work.

The rest of this paper is organized as follows: we first summarize the related work. Next, we propose the computational model for consumer impulsivity, delve into the impulsive tendency in offline and online domains, and give the experiment results. Finally, we present some discussions, and give the conclusion.

RELATED WORK

Consumer Impulsivity Research

Consumer impulsivity, which can also be referred to impulsive buying tendency or unplanned purchasing tendency, has long been studied in consumer behavior, psychology and economics. Extensive research on consumer impulsivity began in the early 1950s and sought to investigate those purchase decisions whether are relatively rapid and subjectively biased in favor of immediate possession [9]. Stern [28] held that impulsivity is manifested when consumers make unplanned purchases or make inferior choices. This view assumes certain types of behavior are rational, and behavior that deviate from the rational ones should be considered as irrational or impulsive. From the theory of reasoned action, the concept of "subjective norm" describes that the perceived social pressure will influence consumer to perform or not to perform the behavior, and thus can lead to impulsive purchase behavior [2]. Applebaum [4] stepped further to suggest that impulsive purchase stems from the consumer's exposure to stimuli and the level of impulsivity. It states that consumer impulsive behavior is highly influenced by environment and personal attributes. Actually, our framework conforms to the view proposed by Applebaum, since we consider that if a consumer has received strong stimuli recently and he is an impulsive guy, he will be easily persuaded to buy the product, whether he actually needs the product or not. We consider impulsivity from the environmental stimuli instead of the practical demand.

Over decades, researchers have designed various scales to measure this personal attribute through a structured validation process. The most representative scales are presented in two groups: direct scales and indirect scales. Direct scales aims at measuring a consumer's impulsivity by directly investigating into the consumption intention. The Consumer Impulsiveness Scale presented by Puri [23] (a 12-item self-report questionnaire to classify subjects as prudents, moderates or hedonics) and the scale proposed by Rook and Fisher [25] (a 9-item self-report questionnaire that assumes impulsive buying ranges from relative neutrality to either strong disapproval or encouragement) are included in this category. Indirect scales, which are originally designed to measure general impulsivity trait in psychology, can also be applied to assess consumer impulse buying tendency. Typically, BIS [5] and UPPS [30] are included in this category, where BIS is a 20-item self-report questionnaire that is designed to assess dispositional sensitivities and UPPS is a 45-item self-report questionnaire that is designed to measure impulsivity across dimensions of the Five Factor Model of personality.

Compared to previous work, our work primarily differentiates in two ways: 1) we explore consumer impulsive tendency in consideration of stimuli from social network posts; 2) we develop a data-driven framework to figure out consumer impulsivity computationally and automatically.

Social Influence and Consumer Behavior

Purchasing decisions are often strongly influenced by people who the consumer knows and trusts in both online and offline context [17]. Sinha and Swearingen [27] found that consumers are far more likely to accept recommendations from people they know and trust, e.g., friends and family members, rather than from automated systems on e-commerce websites. Bhatt et al. [7] empirically demonstrated that a consumer's friends exercise "peer pressure": if friends widely adopt a product, the consumer is more likely to buy it. Guo et al. [16] also showed that consumers are more likely to purchase from sellers that friends in their network have already bought from, according to the transaction history on the e-commerce social network site Taobao. Enders et al. [11] discovered that social network sites including Twitter and Facebook are driving forces behind increasing volume of traffic to retail sites.

Compared with previous influential work primarily aimed at the influence of social networks' structure and interaction on consumer behavior, we step further to consider the stimuli of impulsive buying behavior from social network posts and investigate consumer impulsivity which is particularly crucial for personalized recommendation and target marketing.

MODELING GENERAL CONSUMER IMPULSIVE

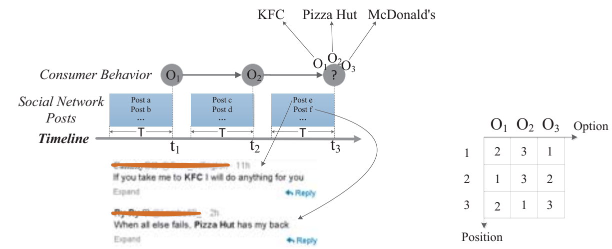
In this section, we present a general model to explore consumer impulsivity implied by an individual's consumption activities and the perceived stimuli from social networks. At first, we explicitly clarify some terms commonly used in this article, and then tackle the challenge of modeling and inferring consumer's impulsivity.

Preliminary

Point of Interest (POI): A POI p refers to a specific point location that someone may find useful or interesting. It is described by an id, a latitude, a longitude, and a category (such as restaurant, shopping mall, etc.).

Check-in: Check-in is that a person announces his arrival at a POI on location based social network service such as Foursquare. A check-in record c is a triple $\langle u, p, t \rangle$ which indicates user $c.u$ visited POI $c.p$ at the particular time $c.t$.

Action and **Option**: An action x taken by a consumer is a domain-specific consumption activity, which discriminately describes the observable activity of this consumer in one certain domain at a specific time. $x \in \{o_1, \ldots, o_M\}$ indicates an option provided for an action, the granularity of the option can vary according to different demands and the data format obtained from the data provider. For example, an action on Foursquare refers to a check-in in the offline consumption domain, where the option can be represented with a POI or a POI category; an action on Amazon refers to the purchase of a product in the online shopping domain, where the option can be the exact product or the product category, e.g., "skincare". The action sequence $\boldsymbol{x} = (x_1, x_2, \ldots, x_N)$ of a consumer refers to the actions taken in chronological order, where N is the number of actions.



(a) Action, option and visible social network posts with regard to a consumer (b) *DOS* matrix.

Figure 2. Consumer behavior, social network stimuli, and an example of *DOS* matrix

Social Network Stimuli and **Dynamic Option Stimuli** (***DOS***): For an action taken by a consumer at time t, the social network stimuli refers to the visible posts (e.g., the posts published by this consumer's friends) on social network in the period $[t - T, t)$, where T is a parameter which indicates that we are concerned with posts falling in T days before an action. As shown in Figure 2(a), given a consumer facing several options at the last position t_3, the visible posts from social network in the period $[t_3 - T, t_3)$ form the perceived stimuli and might provide incentive for the final decision. ***DOS*** is an $N \times M$ (length of sequence $\times$ number of options) matrix, where each element is an integer ranging from 1 to M. At each position of the action sequence, the consumer faces M options, and the comparison among the stimuli intensity related to these options at that moment determines a partial order (assume we have pre-computed the stimuli intensity related to each option triggered by the posts at each position, the computation detail will be discussed in next section). Thus we use ***DOS*** to represent the comparison at each position, where the ith row measures the partial order of M options at the ith position of the action sequence. For example, Figure 2(b) shows at the $3rd$ position, o_3(McDonald's) $>$ o_1(KFC) $>$ o_2(Pizza Hut), which implies the stimuli intensity related to McDonald's is the strongest while that related to Pizza Hut is the weakest during that period.

Consumer Impulsivity Level: The consumer impulsivity level $z \in \{1, 2, \ldots, K\}$ is an instantaneous state related to one action, and it varies over time. A larger value points to a higher impulsive propensity in the consumption activities and vice versa. At each position of the action sequence, both the consumer impulsivity level and the stimuli intensity of an option determine a consumer's acceptance for that option. For example, if a consumer has a high impulsivity level at a position, she is more impulsive at that time and thus easily persuaded by the option with a high stimuli intensity, e.g., M-

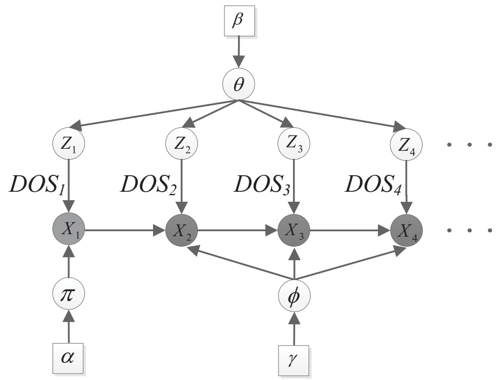


Figure 3. A graphical representation of our general consumer impulsivity model. X represents observation, Z, π, ϕ, θ represent hidden variables, and α, β, γ represent hyperparameters.

Table 1. Summary table of symbols, where "dictated" indicates parameters that are pre-defined, "observed" indicates variables are directly observed from data, "learned" indicates parameters that are learned in our model.

Symbol	Description
K	number of optional values for consumer compulsivity level (dictated)
M	number of options for an action (observed)
N	length of action sequence (observed)
$O = \{o_1, \ldots, o_M\}$	option set (observed)
$\boldsymbol{x} = (x_1, \ldots, x_N)$	action sequence (observed)
$\boldsymbol{z} = (z_1, \ldots, z_N)$	consumer impulsivity level sequence (learned)
$DOS_{N\times M}$	dynamic option stimuli matrix (observed)
$\boldsymbol{\theta} = \{\theta_1, \ldots, \theta_K\}$	consumer impulsivity level distribution (leanred)
$\boldsymbol{\pi} = \{\pi_1, \ldots, \pi_M\}$	initial utility distribution (learned)
$\boldsymbol{\phi}_{M\times M}$	utility transition matrix (learned)
$\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma}$	hyperparameters (dictated)

cDonald's which is frequently discussed by friends on social networks during that period.

Consumer Impulsivity Attribute (*CIA*): *CIA* is a real number ranging from 1 to K, which is the mean of a categorical distribution $\boldsymbol{\theta} = \{\theta_1, \ldots, \theta_K\}$, where θ_k points to the probability of having consumer impulsivity level k. *CIA* measures the temperament, which is implied by the integrated behavior a consumer has conducted. The larger the *CIA*, the greater impulsive propensity the consumer possesses and vice versa.

Consumer Impulsivity Model

How are a consumer's observable actions generated sequentially? We tackle this problem in consideration of both option utility [22] (can also be regarded as consumer's preference for option) and impulsivity [4]. To address this issue, we leverage a graphical model to express the procedure of generating observable actions. All the symbols used in this model are summarized in Table 1. As shown in Figure 3, latent variable $\boldsymbol{\pi}$ is the initial utility distribution, which can be interpreted as the initial probability of choosing each option and latent variable $\boldsymbol{\phi}$ is the utility transition matrix, which can be interpreted as the first-order conditional probability between options (higher order will bring more parameters and thus exacerbate the data sparsity problem. In addition, learning more parameters will also reduce efficiency. Thus we use first-order transition matrix as a tradeoff between effectiveness and efficiency). $\boldsymbol{\pi}$ and $\boldsymbol{\phi}$ characterize the Markov process widely adopted in the sequential behavior model. In addition, Z_i is a latent variable that points to the consumer impulsivity level at position i and we assume each consumer impulsivity level is sampled from the categorical consumer impulsivity level distribution $\boldsymbol{\theta}$. X_i is a variable which points to the observable option for the ith action, the value of X_i is dependent on previous chosen action x_{i-1}, utility transition matrix $\boldsymbol{\phi}$ (or initial utility distribution $\boldsymbol{\pi}$), consumer impulsivity level z_i, and the dynamic option stimuli matrix ***DOS***. Given that ***DOS*** has been precomputed, the conditional probability is given as

$$P(X_i = x_i | x_{i-1}, z_i, \boldsymbol{\phi}) = \frac{f(x_i, x_{i-1}, z_i, DOS_{ix_i})}{\sum_{x\in O} f(x, x_{i-1}, z_i, DOS_{ix})}, \tag{1}$$

Actually, we expect that at each position, when a consumer is at a higher impulsivity level, she is more likely to be primed for accepting an option with a larger stimuli intensity, and the option utility is more likely to be neglected in this case; however, when she is at a lower impulsivity level, in this situation, she is more likely to choose an option according to the option utility. Given above, we consider the following function,

$$f(x, x_{i-1}, z_i, DOS_{ix}) = \phi_{x_{i-1},x}^{\frac{K-z_i}{K}} \cdot DOS_{ix}^{\frac{z_i-1}{K}}, \tag{2}$$

For expressive convenience, the row $\{\phi_{x_0x_1}, \ldots, \phi_{x_0x_M}\}$ is used to represent initial utility distribution $\boldsymbol{\pi}$.

Specifically, the generative process of our consumer impulsivity model (**CIM**) is as follows:

1. Draw initial utility distribution $\boldsymbol{\pi} \sim$ Dirichlet($\boldsymbol{\alpha}$).
2. For the mth row in utility transition matrix $\boldsymbol{\phi}$, draw $\boldsymbol{\phi}_m \sim$ Dirichlet($\boldsymbol{\gamma}_m$).
3. Draw consumer impulsivity level distribution $\boldsymbol{\theta} \sim$ Dirichlet($\boldsymbol{\beta}$).
4. For the ith position in the sequence,
   (a) draw consumer impulsivity level $z_i \sim \boldsymbol{\theta}$,
   (b) draw $x_i \sim P(X_i | x_{i-1}, \boldsymbol{\phi}, z_i)$.

Inference and Prediction

A wide variety of algorithms such as Gibbs sampling and EM algorithm can be applied to perform inference in graphical models. Following [14] for topic model inference and [26] for HMM inference, we apply explicit pointwise Gibbs sampling by repeatedly drawing consumer impulsivity level z, consumer impulsivity level distribution $\boldsymbol{\theta}$, and utility transition matrix $\boldsymbol{\phi}$. The sampling procedure is summarized as follows:

Given the current state of the sampler, $\{\boldsymbol{z}, \boldsymbol{\theta}, \boldsymbol{\phi}\}$, iteratively for each position i,

1. Randomly draw z_i from

$$\begin{aligned} P(z_i | \boldsymbol{z}_{-i}, \boldsymbol{x}, \boldsymbol{\phi}, \boldsymbol{\theta}) &\propto P(\boldsymbol{z}, \boldsymbol{x} | \boldsymbol{\phi}, \boldsymbol{\theta}) \\ &\propto \theta_{z_i} \cdot f(x_i, x_{i-1}, z_i, DOS_{ix_i}). \end{aligned} \tag{3}$$

2. Randomly draw $\boldsymbol{\theta}$ from

$$\boldsymbol{\theta} \sim \text{Dirichlet}(\boldsymbol{\theta}|\boldsymbol{\beta}'), \tag{4}$$

where $\boldsymbol{\beta}'$ is a vector that increases the position k by n_k for $\boldsymbol{\beta}$, n_k is the number of consumer impulsivity level with value k in the current state of the sampler.

3. For the mth row in utility transition matrix $\boldsymbol{\phi}$, randomly draw $\boldsymbol{\phi}_m$ from

$$P(\boldsymbol{\phi}_m|\boldsymbol{z},\boldsymbol{x},\boldsymbol{\theta}) \propto P(\boldsymbol{x}|\boldsymbol{\phi}_m,\boldsymbol{z}) \cdot P(\boldsymbol{\phi}_m|\boldsymbol{\gamma}_m) \propto \frac{\prod_{i\in\{x_{i-1}=m\}} f(x_i, x_{i-1}, z_i, \boldsymbol{DOS}_{ix_i})}{\prod_{i\in\{x_{i-1}=m\}} \sum_{x\in O} f(x, x_{i-1}, z_i, \boldsymbol{DOS}_{ix})}. \tag{5}$$

To sample vector $\boldsymbol{\phi}_m$ from the pseudo probability in Eq. (5), we use Gibbs sampling again and iteratively apply the rejection sampling method [12] to sample ϕ_{mj} from conditional probability $p(\phi_{mj}|\boldsymbol{\phi}_{m,-j})$.

Each iteration corresponds to a traverse of all positions in this consumer's action sequence. The inference algorithm runs multiple iterations until stop criteria satisfies, then we obtain updated consumer impulsivity level distribution $\boldsymbol{\theta}$, and the *CIA* of this consumer is represented as the mean of $\boldsymbol{\theta}$. Next, to predict the next action x_{N+1} (we will test the prediction performance in the experiment part), the conditional probability of X_{N+1} is given as

$$P(X_{N+1} = x|x_N, z_i, \boldsymbol{\phi}, \boldsymbol{\theta}) = \sum_{k=1}^{K} (\theta_k \cdot \frac{f(x, x_N, k, \boldsymbol{DOS}_{(N+1)x})}{\sum_{x\in O} f(x, x_N, k, \boldsymbol{DOS}_{(N+1)x})}), \tag{6}$$

CONSUMER IMPULSIVITY IN TWO SPECIFIC DOMAINS

In this section, we discuss consumer impulsive behavior in two specific domains: offline and online consumption activities.

Consumer Impulsivity in Offline Consumption

In recent years, the blooming development of smart cards and mobile devices has offered the opportunity to gain insight on consumer offline behavior at an unprecedented scale, using data from credit cards [15], mobile payment [3], or location-based social network (LBSN) [32]. In particular, for offline consumption, we investigate a consumer's impulsivity according to the check-ins and the visible posts on Sina Weibo, which is the most popular social network website in China and also provides location-based services such as check-in.

On the one hand, the check-ins of a consumer contain abundant information of her in-store consumption in daily life, e.g., POI indicates the geo-location and shop category where she consumes, while the timestamp reveals the chronological order. Note that some check-ins are not related to consumption activity, e.g., check-ins which are in the residential area or office building. Thus we only focus on check-ins related to consumption activity, e.g. check-ins which are categorized into restaurant, shopping or entertainment. On the other hand, a wealth of information embodied in the published posts on Sina Weibo might provide incentive for offline consumption as illustrated in Figure 1. In consideration of the following/follower mechanism on Sina Weibo (like Twitter, the social relationship is unidirectional), we regard all posts published by an individual's following friends as information she can access on this social network. Thus these posts published by her following friends form the source of stimuli for impulsive purchasing behavior.

For check-in behavior, the time-ordered check-in history of a consumer corresponds to her consumption action sequence in our general model. Since consumer impulsivity measured at different granularities of the observation might reflect impulsive purchasing behavior related to different aspects, we explicitly investigate a consumer's *CIA* in consideration of POI and POI category, respectively.

Figure 4. An example of a post is discussing a POI, but does not contain the POI title completely

If we consider that the option corresponds to the POI (the finest granularity described as a unique ID, a title, and a category), then the observable consumption sequence corresponds to the POI sequence. To estimate the stimuli intensity a post provides for a POI, we consider whether the post is discussing this POI. The most direct method is to test whether the POI title completely appears in the post. However, due to problems with name resolution [13], a post might be discussing a POI but does not incorporate the full POI title. Figure 4 shows a post that does not contain the corresponding restaurant's full name "Artichoke Basille's Pizza". Hence, we compute the similarity between the post and the POI title, and then use this similarity to represent the stimuli intensity. More specifically, given post q and POI p, suppose Q and P are the sets of segmented words in the post's content and the POI title, respectively. According to the various similarity metrics between short texts presented in [33], we adopt a modified overlap similarity between q and p calculated as follows:

$$\text{Sim}(q,p) = \frac{|Q \cap P|}{|Q|}, \tag{7}$$

We consider the visible posts which are published T days before the time of a check-in, then the stimuli intensity for POI p at that moment is given as

$$\text{Stimuli Intensity}(p) = \sum_{t=1}^{t=T} \frac{\sum_{q\in \text{Post}_{-t}} \text{Sim}(q,p)}{e^{\lambda t}}, \tag{8}$$

where Post_{-t} refers to the posts which are published by this consumer's following friends on a social network t days before the check-in, and $e^{\lambda t}$ (λ is a non-negative real number) refers to the decay factor which indicates the more recent the post, the stronger stimulation it can provide. At each position i, we calculate the stimuli intensity for a POI according to Eq. (8) and then sort all the optional POIs based on the stimuli intensity value to obtain the ith row of matrix $\boldsymbol{DOS}$.

If we consider that the option is related to the POI category, then the observable sequence corresponds to the category sequence. The category information explicitly indicates the activity engaged in at that place and we can acquire a better understanding of a consumer's impulsive purchase related to her lifestyle. For example, if a consumer sees many recent posts that talk about Chinese food, even though she does not patronize the restaurants mentioned in those posts (the reason might be that these restaurants are far away), she might be drawn to visit another Chinese restaurant close to her residence. Such behavior implies that she might be an impulsive consumer in the situation of POI category. The stimuli intensity for category C is aggregated by the stimuli intensity for POIs belonging to this category, and the calculation is given as

$$\text{Stimuli Intensity}(C) = \sum_{p \in \text{POI}_C} \text{Stimuli Intensity}(p), \quad (9)$$

where POI_C refers to POIs belonging to category C. The construction of matrix ***DOS*** is similar to the process in the situation of POI.

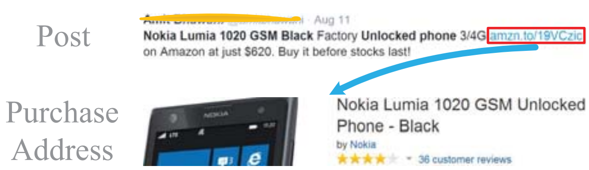


Figure 5. An example that an advertisement is embedded in a social network post, the short url links to the purchase address on the e-commerce website

Consumer Impulsivity in Online Consumption

With the development of e-commerce, a growing number of people have grown used to online consumption due to its convenience and diversity. In addition, the proliferation of social commerce also assists in consumer's online purchase. For example, Figure 5 shows that an advertisement is embedded in a social network post, which can directly guide audiences to the purchase address on the e-commerce website. The statistics of website traffic also indicates that consumers usually visit Sina Weibo right before they access Taobao[1], which implies social network is an importance entry point to online purchase. Specifically, for online consumption, we explore the consumer impulsivity by investigating online shopping behavior on Taobao and visible posts on Sina Weibo.

The description of a purchased product on Taobao typically contains the product name, category, brand, price, seller information, and product summary. The online purchase history provides an in-depth understanding of consumer's status, e.g., the product category indicates demand and interest, the price implies financial situation, and the rating refers to satisfaction, etc. The posts an individual can access are also limited to the posts published by her following friends on Sina Weibo. Moreover, how a consumer's purchasing behavior on Taobao is connected to her post reading history on Sina Weibo will be discussed in the experiment part.

[1]http://www.alexa.com/siteinfo/taobao.com

For online shopping behavior, a consumer's time-ordered purchase history corresponds to her action sequence described in the general model. We also investigate *CIA* related to online shopping in the situation of product and product category, respectively. The stimuli intensity calculation, as well as the construction procedure of ***DOS*** for both product and product category is similar to that presented in check-in behavior (product name corresponds to POI title, product category corresponds to POI category).

EXPERIMENTS

Data Collection and Description

We measured consumer impulsivity *CIA* and evaluated our model **CIM** on two publicly available websites: Sina Weibo and Taobao.

(a) Binding Taobao account to Sina Weibo on the Taobao settings page

(b) A post on Sina Weibo refers to the binding

Figure 6. Connecting Taobao account to Sina Weibo

To explore a consumer's *CIA* in check-in behavior, since her check-ins and visible posts are both recorded on Sina Weibo, the connection of consumer behavior and social network stimuli can easily be finished by identifying her Sina Weibo account. However, to investigate a consumer's *CIA* in online shopping, we need to connect her Taobao account to her Sina Weibo account. As shown in Figure 6(a), a consumer can explicitly connect her Taobao account to her Sina Weibo account on the Taobao settings page. After the connection procedure, the system will recommend that the consumer publish a post on Sina Weibo by default. Figure 6(b) shows this post contains unique keywords "I have just bound my account on Taobao", hence we used the "tweet content search" function on Sina Weibo to find consumers who explicitly published such posts. The short url in the post indicates this consumer's Taobao personal page, thus we can connect her Sina Weibo account to her Taobao account.

Figure 7. A consumer's partial obtained ratings from sellers. Each record contains product title, rating time and the seller description.

Sina Weibo, the largest social network in China, also provides location-based services. By using public APIs, we crawled a consumer's information including her profile description, following friends, all the posts published by these friends, and all check-in histories with timestamp and POI details. Then we used these posts as the stimuli source to compute the ***DOS*** matrix at different granularities and in two domains. To collect a consumer's online shopping data on Taobao, we crawled the publicly available credit ratings related to Taobao consumption, which is representative of his purchase history. Specifically, if a consumer has purchased a product on Taobao, the seller will rate this consumer actively to show her appreciation of the transaction, or passively according to default rating rules[2]. All ratings will be shown on the consumer's credit rating page. An example of a consumer's partial ratings from several sellers are shown in Figure 7, where each record contains the purchased product, rating time, and corresponding seller. These rating records explicitly obtained from sellers represent this consumer's online purchase history. Since a rating is usually given right after the purchasing behavior, we regard the rating time as the purchase time. We also crawled each product's detailed information such as category and specification by using the APIs Taobao provides. Furthermore, to verify whether the rating records accurately represent a consumer's complete purchase history on Taobao, we asked 25 persons (7 of them come from universities, and the others work in different industries) to provide the coverage of products in the ratings by comparing with the actual total number. The results reveal that the average coverage was 86.4%, which we believe is representative enough of a consumer's online shopping behavior.

For check-in behavior, we focus on consumers who reside in Beijing or Shanghai according to the profile description. For online shopping behavior, we focus on consumers who explicitly connect their Taobao account with Sina Weibo. Furthermore, to clean up the data, we first filter the noisy data, e.g., repeated check-ins at the same place in quite a short interval or check-ins that do not belong to consumption activity, then we keep those users on Sina Weibo who have at least 50 check-ins and those users on Taobao who have at least 50 purchases. The basic statistics of the dataset are summarized in Table 2, e.g., for check-in data, "#Avg. Check-in" and "#Avg. POI" indicate that a consumer would have 87.4 check-ins while visit 57.3 different POIs on average, "#Avg. Daily Posts" indicates a consumer would read 289.4 posts published by her following friends on Sina Weibo per day. For the POI category, we focus on the second level, which gives a comprehensive representation of consumer behavior, such as "Chinese restaurant", "shopping mall", "cinema", etc. For online shopping, we consider product category description at the first level, which contains 112 types in total, the typical examples are "woman's wear" and "leisure wear".

Experiment Settings

We briefly introduce the experiment settings in this subsection. When exploring the **CIM** model for a consumer, we pre-computed the ***DOS*** matrix on top of her possible options and visible posts (taking DOS@POI for example, at each position i, we calculate the stimuli intensity for a POI according to Eq. (8) and then sort all the optional POIs based on the stimuli intensity value to obtain the ith row of matrix ***DOS***), and then obtained her *CIA* according to the inference procedure. Following the five-point partition of impulsive purchase tendency adopted in [25], we set the number of optional values for consumer impulsivity level as $K = 5$. Thus for a consumer, $CIA = 5$ implies she has the highest impulsive tendency, while $CIA = 1$ implies she is the hardest to be persuaded. Furthermore, by using a grid search according to the best average prediction performance of all situations discussed in the following prediction performance part, the hyperparameters $(\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma})$ mentioned in Table 1 are set as $\boldsymbol{\alpha} = (0.4, \ldots, 0.4)$, $\boldsymbol{\beta} = (0.2, \ldots, 0.2)$, $\boldsymbol{\gamma} = (0.2, \ldots, 0.2)$.

[2] http://service.taobao.com/support/knowledge-882172.htm

Table 2. Basic statistics of the collected dataset. Check-in dataset is from Sina Weibo, and Online shopping dataset is from Taobao.

Domain	Statistics	
Check-in	#Consumer	7,528
	#POI	59,515
	#Category (Second Level)	54
	#Avg. Check-in	87.4
	#Avg. POI	57.3
	#Avg. Category	14.1
	#Avg. Daily Browsed Posts	289.4
	#Total Posts	466,221,084
Online Shopping	#Consumer	8,217
	#Product	748,852
	#Category (First Level)	112
	#Avg. Purchase	153.8
	#Avg. Product	121.5
	#Avg. Category	23.7
	#Avg. Daily Posts	304.2
	#Total Posts	522,418,782

Consumer Impulsivity

In this subsection, each user's *CIA* is inferred by setting the parameters in Eq. (8) as $T = 5$ and $\lambda = 0.4$ (due to the best average performance of all situations discussed in the following prediction performance part). First, we compare *CIA* with a survey-based result for a group of users. Next, we analyzed *CIA* distribution at different granularities and in two specific domains. Finally, we investigated the correlation between consumer's *CIA* and demographic factors.

CIA and Survey-based Result

To compare our inferred *CIA* with traditional survey result, we need the users in our dataset to fill an impulsivity survey. First, we translate the widely adopted impulsive purchase tendency scale[3] mentioned in [25] into Chinese[4]. This scale has 9 items, and each item has 5 optional responses, which range from "strongly disagree" (the lowest score 1) to "strongly agree" (the highest score 5). The average score of these items reflects the degree of a consumer's impulsivity, where 5 indicates the highest while 1 indicates the lowest. Next, in the online shopping dataset, we found 976 consumers who published their email addresses on their Sina Weibo personal pages (actually in the check-in dataset, we only found 21 consumers who published their email addresses. This number is too small and we ignored these consumers). Then we sent invitations to these consumers, and 103 of them returned in the end (56 males and 47 females).

To reveal the correlation between our inferred *CIA* and survey results, we computed Pearson correlation between *CIA*

[3] http://1drv.ms/1tvYTXn
[4] http://1drv.ms/1Eo4m7f

Table 3. The Pearson correlation, as well as related P-Value, between *CIA* and survey results

	Pearson Correlation	P-Value
Survey Results vs. *CIA*@Product	0.246	0.007
Survey Results vs. *CIA*@Product Category	0.551	$< 10^{-10}$

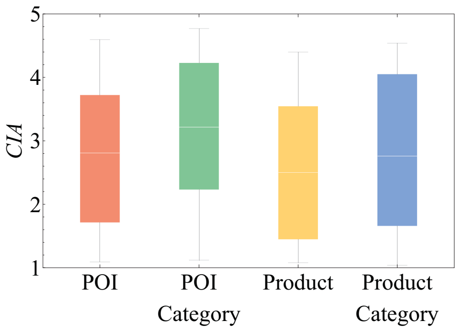


Figure 8. *CIA* distribution in various situations. For each bar, we first calculate each user's CIA in that situation, and then plot the box distribution for all users.

and survey results. Furthermore, since the correlation results are based on a small sample (considering that this survey is extremely difficult because it aims at the particular users who must meet three conditions: 1) being covered in our online shopping dataset, 2) having explicit email information, and 3) being willing to finish a online survey. Thus only 103 users responded and filled the survey table), we apply permutation test[5] to validate the significance of the results, which are shown in Table 3. The small P-Values show that our inferred *CIA* at different granularities has a significant statistical correlation with the survey results. However, the correlation in the situation of product is quite low and that in the situation of product category is much higher. The reason might be that in the product situation, it is difficult to match POI and post (most of stimuli intensity is 0), the DOS matrix is too sparse to reflect consumer impulsivity sufficiently. More interestingly, we also found that a user reported she was not impulsive in the survey table (average score is 1.3, which ranks 97th of the 103 participants), however, her *CIA* is quite high (*CIA* is 4.1, which ranks 3rd of the 103 participants) because she did purchase products which are related to the recently visible posts on social network. This kind of situation implies that our data-driven method is more effective in discovering a user's impulsivity, while the survey-based results might suffer from some limitations such as being vulnerable to memory.

Analysis of CIA Distribution

Figure 8 gives an intuitive display of *CIA* distribution of all users at different granularities and in two domains. It shows that *CIA* in the situation of POI or product is lower than that in the situation of corresponding category, and most people tend to show a low impulsive purchase tendency. On the one hand, the social network stimuli provided in the situation of POI or product might be insufficient in revealing a consumer's entire impulsivity, because impulsive purchasing behavior might be triggered by the stimuli from other channels, e.g., TV advertisements, offline promotions, etc. On the other hand, the stimuli aggregated at the category might provide enough incentive for a consumer's choice, e.g., even though a consumer would not be easily persuaded to accept Little Sheep Hot Pot (a specific hot pot shop) which appears multiple times on social network, but if many of her friends discuss hot pot, she might be attracted to try a hot pot shop. This figure also shows that *CIA* in the situation of product is a little lower than that in the situation of POI, the reason might be that the social network stimuli related to Taobao products are even weaker than those related to POI. Furthermore, we found that consumers with a high *CIA* are obviously influenced by the social network stimuli, e.g., a consumer with *CIA* 4.1 in the situation of POI visited Qing-Feng Steamed Dumpling Shop immediately right after many of her following friends discussed the event mentioned in Figure 1, even though she had never been to that shop until then.

[5]Permutation test especially aims at the small-size sample. The distribution of the test statistic under the null hypothesis is obtained by calculating all possible values of the test statistic under rearrangements of the labels on the observed data points.

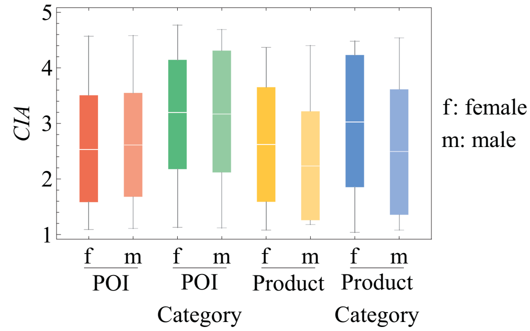


Figure 9. *CIA* distribution w.r.t gender. For each bar, we first calculate each user's CIA in that situation, and then plot the box distribution for users with the related gender.

Table 4. Pearson correlation, as well as related P-Value, between age and *CIA*

Granularity	Coefficient	P-Value
POI	-0.431	$< 10^{-10}$
POI Category	-0.373	$< 10^{-10}$
Product	0.034	0.118
Product Category	-0.296	$< 10^{-10}$

CIA and Demographics

The influence of demographic factors on consumer's impulsive buying behavior has been widely discussed in previous research [6]. We recorded consumers' demographic attributes including age and gender by crawling their profile pages on Sina Weibo. As shown in Figure 9, in the situation of product or product category, the *CIA* of a given female is significantly higher than that of a given male. This result is consistent with the result in [20], which reported that females indicated more impulsive buying than did males. It implies that the female is the primary focus in the associated marketing strategy of e-commerce. The figure also shows that for check-in behavior, there is no significant difference in terms of gender. To uncover the relationship between age and *CIA*, we computed Pearson correlation and applied permutation test as shown in Table 4. It indicates that in the situation of POI and both two categories, the *CIA* declines as age increases, which is contrary to the reported results in [20]. The inconsistency of results related to age might be reasoned that [20] focused on adolescents aged from 15 to 19, while consumers in our data have a larger age range, which is from 14 to 81. With the increase of age, the adolescents are more financially independent and thus they can spend money more impulsively as they want. However, from the aspect of a wider age range, older consumers are more rational and they are better at controlling impulsive spending.

Prediction

In this subsection, we evaluate the prediction performance of **CIM** in various situations.

Taking check-in in the situation of POI as an example, to evaluate the prediction performance of **CIM**, the experiment was designed as follows: the check-in history of a consumer is split into a training portion (90%) and a testing portion (10%) in chronological order. We trained our model on the consumer's training portion and then obtained the prediction probability for a given check-in in the testing portion as described in Eq (6). Given the options ordered by the prediction probability, we used nDCG, a widely adopted metric in information retrieval, to evaluate the performance in the experiments. We first listed prediction probabilities of optional candidates in ascending order, and used rel_i as a binary value indicating whether the ith predicted POI was the one visited by the user. Then we used nDCG@p to evaluate the performance, which is given as

$$\begin{aligned} &\mathrm{nDCG@p} = \frac{\mathrm{DCG_p}}{\mathrm{IDCG_p}}, \\ &\text{where} \quad \mathrm{DCG_p} = \sum_{i=1}^{p} \frac{2^{rel_i} - 1}{\log_2 i + 1}, \end{aligned} \tag{10}$$

where $\mathrm{IDCG_p}$ is the value of $\mathrm{DCG_p}$ for the perfect ranking. A larger value of nDCG@p indicates a better prediction performance and vice versa. We compared our model against the following methods:

1. **OF** (Order by Frequency): This method always gives a recommendation list of POIs according to the consumer's visit frequency in the past.

2. **MC** (Markov Chain): This method models sequential behavior by learning a transition graph over POIs that is used to predict the next check-in based on the recent check-ins of a consumer. The recommendation list is then ordered by transition probability given the previous location.

3. **CRF** (Conditional Random Field): This method applies a CRF model [19] takes the POI transition as well as POI stimuli intensity (calculated according to Eq. (8)) into consideration. To be more specific, for each user, the chosen POI is treated as the hidden variable, and the POI-intensity vector is treated as the observation (each element is the stimuli intensity to the corresponding POI).

4. **FPMC** (Factorized Personalized Markov Chain): This method proposed by [24] is a factorization model embedding users' latent preferences and their personalized Markov chains to provide the next POI recommendation. In our reported results, the factorization dimension was set at 20 for comparison.

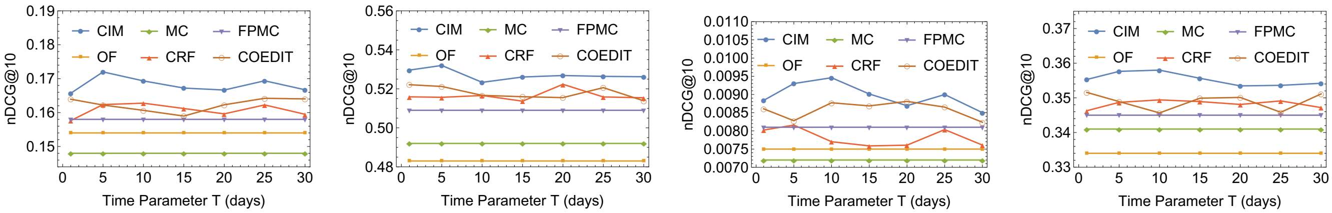
5. **COEDIT** (Collaborative Editing based Domain and Item Transfer): This method presented in [31] applied transfer learning to reduce the data sparseness in the collaborative filtering problem by involving an auxiliary information source. In our scenario, for each user, we first computed the stimuli intensity (calculated according to Eq. (8)) for each POI. Then we build the user-POI matrix which is similar to the user-item matrix in the auxiliary information source [31], where each element in the user-POI matrix indicates the calculated POI stimuli intensity for the user. In our reported results, the latent dimension was set at 20 for comparison.

Note that the inputs for **OF**, **MC** and **FPMC** are only check-ins, and the inputs for **CRF** and **COEDIT** contain both check-ins and social network posts.

For the two parameters in Eq. (8), which tune the stimuli intensity according to time, we first set decay factor λ as 0.4 and change the concerned days T from 1 to 30, and show the nDCG@10 trend in Figure 10. We can see our model **CIM** generally obtain a good performance when T is set as 5. Next, we set concerned days T as 5 and change the decay factor λ from 0 to 1, and show the nDCG@10 trend in Figure 11. Generally, our method **CIM** have a good performance when λ is set as 0.4. From both Figure 10 and Figure 11, it is clear that our model outperforms the baselines in various situations. Our method exceeds **OF**, **MC** and **CRF** because that the characteristics of option frequency, transition probability, as well as stimuli intensity has already been captured by our model. Our model outperforms **FPMC** because that **FPMC** actually considers the latent relationship among consumers' behavior while our model considers consumer's personal attribute and external stimuli, which implies that the usage of social network stimuli is effective in the prediction task. In addition, **COEDIT** transfers the social network stimuli knowledge as a whole while our method investigates into the connection of behavior and social network stimuli at each time point. Thus, in most cases, our model has a better performance than **COEDIT**. Except for the better performance of prediction, we can see that our methods can also give a better explanation for the psychology of decision-making.

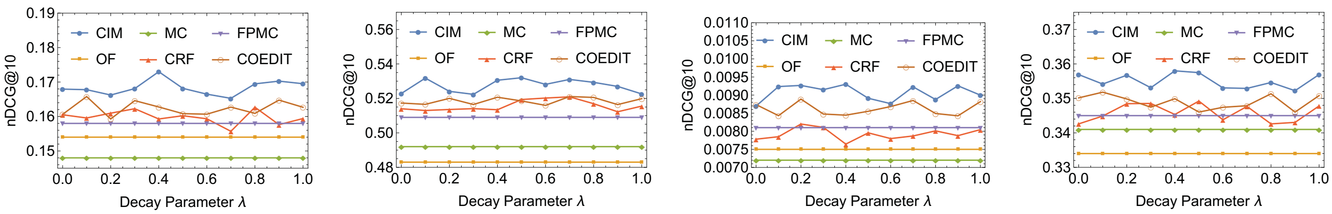
DISCUSSSION

- **Model Design**. We propose consumer impulsivity level and *CIA*. Actually these terms are referred to the traditional scale in consumer impulsivity. These scales have many items, each answer for an item will give a 1-5 score and the final impulsivity score is averaged by these answer scores. Our compulsivity level is similar to a particular answer score, and *CIA*, the mean of a categorical distribution is similar to the average of these answer scores.



(a) POI (b) POI Category (c) Product (d) Product Category

Figure 10. Prediction results nDCG@10 of CIM and all baselines w.r.t parameter T



(a) POI (b) POI Category (c) Product (d) Product Category

Figure 11. Prediction results nDCG@10 of CIM and all baselines w.r.t parameter λ

- **Generalizations and Limitations**. While we consider the stimuli from social networks, our method can be generalized to other stimuli, such as TV advertisements, offline promotions, etc. Various stimuli can be incorporated into the calculation of the ***DOS*** matrix. We are aware that the stimuli provided by social networks are only a small part of a consumer's daily life, if more sources of stimuli can be included, the *CIA* measured by our model can better represent a consumer's impulsivity. Furthermore, our method has several other limitations. First, consumer behavior is complicated. Except for impulsivity and option utility considered in our model, there may be many other factors that affect the final determination of a consumption activity, such as geographic constraint, mood, financial position, etc. We will incorporate more factors into our **CIM** model in the future work. Second, the calculation of stimuli intensity is only based on the similarity of product (POI) title and post content. Future work will be extended to include sentiment analysis of these posts, because positive posts provide incentive for impulsive purchases while negative posts might have the opposite effect. In addition, to compute the perceived stimuli strength, we integrate the visible posts from all the following friends and treat the posts from each friend equally. Actually friends with different social tie strength will have different impact on a user's behavior, and we will further investigate how to incorporate social influence to our consumer impulsivity model. Third, we use the check-in into a store as an indicator for consumption. But a consumer might enter a store without consuming anything. This limitation is from the data level instead of method level.

- **Privacy and Ethical Issues**. We want to re-emphasize that in this work we only collected publicly available data, e.g., posts of following friends and check-ins provided by Sina Weibo APIs, ratings of online shopping published in users' credit rating pages (visible to everyone on the web) and the detailed description of products provided by Taobao APIs. The connection between user accounts was also identified from their self-disclosed content. However, users still might not have enough intention for their published data, and the connection of their different accounts might cause undesired consequences, e.g., a user might not expect her Sina Weibo friends to notice her purchasing history on Taobao. Thus, we suggest that both the users and social network sites re-consider their privacy policy in terms of the linkage between multiple accounts. In addition, even though the measure of impulsivity itself is not related to any ethical issues, we have to mention that there are ethical risks of using consumer impulsivity to interfere with consumer's purchase decision. Thus, we suggest that the consumers should be cautious of the recommendations or advertisements that are related to what they have seen recently.

CONCLUSION

In this article, we have proposed a completely data-driven framework termed **CIM** for exploring consumer impulsivity in consideration of the stimuli from social networks. Following the framework, we have investigated check-in behavior and online shopping behavior to uncover a consumer's *CIA* at different granularities in both offline and online context. The extensive experiments we have conducted validated the effectiveness and flexibility of this framework.

Please note that our work is not designed to replace traditional methods of consumer impulsivity. Instead, we believe these methods can complement each other to enable a better understanding of consumer impulsivity, which is not only important for advancing the understanding of consumer impulsivity in consumer behavior science, but also essential to personalized service.

REFERENCES

1. Ainslie, G. Specious reward: a behavioral theory of impulsiveness and impulse control. *Psychological bulletin 82*, 4 (1975), 463.
2. Ajzen, I. The theory of planned behavior. *Organizational behavior and human decision processes 50*, 2 (1991), 179–211.
3. Amoroso, D. L., and Magnier-Watanabe, R. Building a research model for mobile wallet consumer adoption: the case of mobile suica in japan. *Journal of theoretical and applied electronic commerce research 7*, 1 (2012), 94–110.
4. Applebaum, W. Studying customer behavior in retail stores. *The Journal of Marketing 16*, 2 (1951), 172–178.
5. Barratt, E. S. Anxiety and impulsiveness related to psychomotor efficiency. *Perceptual and motor skills 9*, 3 (1959), 191–198.
6. Bashar, A., Ahmad, I., and Wasiq, M. A study of influence of demographic factors on consumer impulse buying behaviour. *International Journal of Marketing and Management Research 4*, 3and4 (2013), 64–76.
7. Bhatt, R., Chaoji, V., and Parekh, R. Predicting product adoption in large-scale social networks. In *Proceedings of the 19th ACM international conference on Information and knowledge management*, ACM (2010), 1039–1048.
8. Chant, J. F. Irrational behavior and economic theory: a comment. *The Journal of Political Economy 71*, 5 (1963), 505–510.
9. Clover, V. T. Relative importance of impulse-buying in retail stores. *The Journal of Marketing 15*, 1 (1950), 66–70.
10. Dell'Osso, B., Allen, A., Altamura, A. C., Buoli, M., and Hollander, E. Impulsive–compulsive buying disorder: clinical overview. *Australian and New Zealand journal of psychiatry 42*, 4 (2008), 259–266.
11. Enders, A., Hungenberg, H., Denker, H.-P., and Mauch, S. The long tail of social networking.: Revenue models of social networking sites. *European Management Journal 26*, 3 (2008), 199–211.
12. Gilks, W. R., and Wild, P. Adaptive rejection sampling for gibbs sampling. *Applied Statistics* (1992), 337–348.
13. Gooi, C. H., and Allan, J. Cross-document coreference on a large scale corpus. Tech. rep., DTIC Document, 2004.
14. Griffiths, T. L., Steyvers, M., Blei, D. M., and Tenenbaum, J. B. Integrating topics and syntax. In *Advances in neural information processing systems* (2004), 537–544.
15. Gross, D. B., and Souleles, N. S. Do liquidity constraints and interest rates matter for consumer behavior? evidence from credit card data. *The Quarterly Journal of Economics 117*, 1 (2002), 149–185.
16. Guo, S., Wang, M., and Leskovec, J. The role of social networks in online shopping: information passing, price of trust, and consumer choice. In *Proceedings of the 12th ACM conference on Electronic commerce*, ACM (2011), 157–166.
17. Kim, Y., and Srivastava, J. Impact of social influence in e-commerce decision making. In *Proceedings of the ninth international conference on Electronic commerce*, ACM (2007), 293–302.
18. Knight, J. G., Holdsworth, D. K., and Mather, D. W. Country-of-origin and choice of food imports: an in-depth study of european distribution channel gatekeepers. *Journal of International Business Studies 38*, 1 (2007), 107–125.
19. Lafferty, J., McCallum, A., and Pereira, F. C. Conditional random fields: Probabilistic models for segmenting and labeling sequence data.
20. Lin, C.-H., and Lin, H.-M. An exploration of taiwanese adolescents' impulsive buying tendency. *Adolescence San Diego 40*, 157 (2005), 215.
21. Luo, X. How does shopping with others influence impulsive purchasing? *Journal of Consumer Psychology 15*, 4 (2005), 288–294.
22. Mittal, B., and Lee, M.-S. A causal model of consumer involvement. *Journal of Economic Psychology 10*, 3 (1989), 363–389.
23. Puri, R. Measuring and modifying consumer impulsiveness: A cost-benefit accessibility framework. *Journal of Consumer Psychology 5*, 2 (1996), 87–113.
24. Rendle, S., Freudenthaler, C., and Schmidt-Thieme, L. Factorizing personalized markov chains for next-basket recommendation. In *Proceedings of the 19th international conference on World wide web*, ACM (2010), 811–820.
25. Rook, D. W., and Fisher, R. J. Normative influences on impulsive buying behavior. *Journal of consumer research* (1995), 305–313.
26. Scott, S. L. Bayesian methods for hidden markov models. *Journal of the American Statistical Association 97*, 457 (2002).
27. Sinha, R. R., and Swearingen, K. Comparing recommendations made by online systems and friends. In *DELOS workshop: personalisation and recommender systems in digital libraries*, vol. 106 (2001).
28. Stern, H. The significance of impulse buying today. *The Journal of Marketing* (1962), 59–62.
29. VandenBos, G. R. *APA Dictionary of Psychology.* American Psychological Association, 2007.
30. Whiteside, S. P., and Lynam, D. R. The five factor model and impulsivity: Using a structural model of personality to understand impulsivity. *Personality and individual differences 30*, 4 (2001), 669–689.

31. Xu, Q., Xiang, E., and Yang, Q. Social-behavior transfer learning for recommendation systems. In *Proc. of Workshop on Social Web Mining* (2011).

32. Yang, D., Zhang, D., Yu, Z., and Yu, Z. Fine-grained preference-aware location search leveraging crowdsourced digital footprints from lbsns. In *Proceedings of the 2013 ACM international joint conference on Pervasive and ubiquitous computing*, ACM (2013), 479–488.

33. Yih, W.-T., and Meek, C. Improving similarity measures for short segments of text. In *AAAI*, vol. 7 (2007), 1489–1494.