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Empirical Study of Social Features' Roles in Buyers' Complex Decision Making

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Abstract—**This paper aims at studying the roles of social features (as obtained from social networking sources) in buyers' decision process when they are searching for products to buy. Through close observation of users' objective behavior, we have discovered the importance of different types of social features in supporting users to achieve a confident decision at the end. Improving suggestions are further derived on how to better present the social information and combine them with static product attributes to enhance current online decision supports.**

Keywords-empirical study; social features; Flickr

I. INTRODUCTION

In the area of recommender systems, most attentions have been paid to the utilization of social information (e.g., from Last.fm, Movielens, Delicious) to generate recommendations for low-value, taste-related products (e.g., music, movie, book) [7, 19]. However, few have explored what social information can be optimally exploited to assist users in making complex decisions, such as the searching for a high-value, infrequently experienced product (e.g. a digital camera, a computer). Indeed, for the latter so called high-risk products, most of existing decision systems (see in Related Work) only considered the product's static attributes (e.g. the camera's optical zoom, megapixels) to model users' information needs and seldom have realized the potential impact of social features that can be extracted from social media sites.

Researchers from marketing actually indicate that for different product categories, consumer buying behavior will differ [5,6,16]. As for the complex ones that are expensive and infrequently experienced (e.g., computers, cars, homes), extensive decision-making effort is commonly spent by consumers in seeking information and deciding. Accordingly, researchers from the psychology field describe a two-stage process in such condition, where the depth of cognitive load and information processing varies [8, 17]: *the first stage* is to screen down the number of available alternatives to a reduced consideration set; and *the second stage* is to in-depth examine the selected candidates to obtain the final choice.

In this paper, we are particularly interested in addressing the question of *what*, *when* and *where* different sorts of social information are needed within a user's adaptive decision process and *how* they are processed in combination with products' static attributes. Driven by a recent survey that shows "opinions posted by consumers online" is one of most trusted forms of advertising (over 25,000 Internet consumers in 50 countries [15]), we believe that social content should play important role in users' hybrid decision process in which the decision maker seeks for advices for the purpose of reducing the uncertainty and the amount of information that must be processed to make a decision [4,9]. We expect that through our empirical study, the role can be clearer than ever before, and more importantly design suggestions can be implied to related works on recommender systems, making them more applicable to high-risk product domains.

Specifically, we have explored the role of social content obtained from Flickr, which has recently released the digital camera popularity data (e.g., "most popular cameras", "trends in brands", "trends in camera use", etc.) calculated according to the statistics of Flickr community members who have uploaded photos or videos with a particular camera over a certain time. Through empirical user evaluation, we concretely identified how consumers perceived the data from the site, and whether the social resources would be helpful for them to make a more confident and effective purchase. By the means of this case study, we have aimed to reveal the relationship between social features (i.e., community-generated data) and static product data (i.e., in-born attribute values) in supporting complex decision making.

The following content is organized as follows: section II summarizes related researches on consumer behavior and decision tools; section III highlights our focus on understanding users' social information needs through empirical study, and then introduces experimental materials, participant recruitment and procedure; section IV presents results analysis and findings, followed by design implications and our future work (section V).

II. RELATED WORK

Researchers from marketing refer consumer behavior as the action and decision process of people who purchase goods and services [5,6]. The action starts with the need of a product or a service that arises in the customer's mind and then goes through the process of information searching and product evaluation to lead to purchase decision and post-purchase evaluation. For different product categories, consumer buying behavior will differ [5,6,16]. As for the complex ones that are

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expensive and infrequently experienced (e.g., computers, cars, homes), extensive decision-making effort is commonly spent by consumers in seeking information and deciding. Accordingly, researchers from the psychology field describe a two-stage process in this situation, where the depth of cognitive load and information processing varies: the first stage is to screen down the number of available alternatives to a reduced consideration set; and the second stage is to in-depth examine the selected candidates to obtain the final choice.

The importance of learning consumer behavior has been increasingly realized by researchers in developing decision support systems. For instance, based on the two-stage decision process, [8] demonstrated that recommendation agent (RA) is more useful for the initial screening to increase the quality of consideration set, and the use of comparison matrix (CM) is more effective in facilitating pair-wise product comparisons at the second stage to improve objective decision quality. Knijnenburg *et al.* proved that adjusting the elicitation of users' multi-attribute preferences to their domain knowledge can significantly augment individual satisfaction with the system [10]. [1] proposes an Adaptive Decision Support System architecture (ADSS) aimed at providing information display, searching strategies, and appropriate advice for consumers in different product domains based on a set of pre-defined decision rules. Critiquing-based systems, including dynamic-critiquing, knowledge-based systems and our previous work on tradeoff supports [3,18], have been to allow user feedbacks to example products, in the form of critiques (e.g., "I would like something cheaper", "with faster processor speed"). Mahmood and Ricci further model the conversational process as a sequential decision problem based on the Markov Decision Process (MDP) involving different user states and actions [13].

Unfortunately, related works largely neglect users' actual information needs. In fact, the modeling of user preferences has been mainly established on products' static attribute values (e.g., the camera's optical zoom, megapixels), less on social opinions, although it has been claimed that shoppers tend to wait for early adopters' opinions to reduce the risk of buying a new product [11]. [12] has lately conducted a tentative experiment that measured product ratings and reviews as part of recommendations in influencing users' searching strategies, but it is still not clear what information users do require when they are at different processing stages (e.g., filtering and in-depth evaluation) and how the social influence data can be effectively combined with static product attributes to help the construction of user profile.

III. Our Focus and Experiment Setup

A. Our Focus

Our focus has been on finding answers to the above concerns and particularly aiming at the two objectives: 1) clarifying how users in practice follow the two-stage process to achieve their decision and whether the process would be further refined; 2) at different stages, discovering types of information required by users and especially the roles of social features relative to static ones. With the objectives, we have first classified all possible product information into two categories according to their semantic qualities: **static features** that include all in-born attribute values about the product (e.g., the digital camera's price, weight, megapixels, optical zoom, etc.), and **social features** defined as any data derived from content generated by other consumers. *Product reviews, product popularity*, and *related products* are typical examples of the latter source. Product reviews are directly collected from consumers' post-purchase evaluative feedbacks in form of numerical scores on the product or detailed positive/negative comments written in natural language. Product popularity is reflected in the popularity-based ranking list such as "best sellers", "most wanted", or "top ones under $500". "Related products" indicates a product's relationships with other products, as suggested by consumers' actions (e.g., "shoppers who viewed this one (that is clicked by the current user), also viewed others").

B. Materials

The experimental goal was then to measure users' decision behavior when they are provided with both static and social features related to the scenario product domain (digital cameras), so as to discover these features' respective practical roles. In order to reach the goal, we have decided to observe users' actions when they interacted with Flickr Camera Finder that mainly provides the social community info (see TABLE I). In comparison, a traditional e-commerce site was also provided that primarily displays static product attributes.

TABLE I. Products' Static Features and Social Features Obtained from Flickr Camera Finder (CF) and Yahoo Shopping Sites.

	Social Features	Static Features
Flickr CF (www.flickr.com/cameras/)	Product popularity: "*Most Popular Cameras in the Flickr Community*", "*Top 5 xx Cameras in the Community*", popularity sorting by "*# of items, avg. daily users, activity factor,* etc."; Product usage trend; Product photos: "*Photos taken with the product*"	Each product's four basic attributes: *"camera type", "megapixels", "LCD size", "media type"*
Yahoo CF (shopping.yahoo.com)	Product popularity: "*Top Digital Cameras*"; Product's related products: "*Shoppers who viewed this product also viewed*"; Product ratings/reviews	Eight basic attributes for initial screening and filtering; Each product's full set of attributes (34) and descriptions;

More concretely, the experiment was designed in a free-choice scenario with two sites as options for users to freely choose and examine the product info: Flickr Camera Finder (the product browsing service primarily based on social popularity, www.flickr.com/cameras/) and Yahoo Shopping (as the representative of standard e-commerce websites, shopping.yahoo.com). For the latter site, we have actually investigated a number of popular e-commerce sites including Amazon, Yahoo Shopping, shopping.com, etc, and finally decided on Yahoo Shopping because it shares the same product database with Flickr Camera Finder (CF), and can be also representative of other standard e-commerce sites regarding information amount and diversity. TABLE I summarizes all **static features** and **social features** respectively provided by the two sites.

C. Participants

For each participant, it was planned to take at least two hours with one hour of using the provided product features to perform a task, and another hour of answering the interview questions. We have finally recruited twelve motivated volunteers (three females). They are Master or PhD students in our department with ages between 20 and 40. The perceived risk of buying a digital camera was costly but they can afford, which indicates that the task of asking them to "purchase" a digital camera (see the user task below) can be realistic for them to take the scenario role. Most of them actually expressed interest in buying a digital camera at the time of experiment. All users have online shopping experiences, and many of them (9 users) have bought items at least every three months, but most of frequently purchased items are relatively of low values such as books, accessories, DVDs. When being asked how they usually searched for a high-value product to buy, the majority (10) replied that they often reviewed as much product information as possible in order to ensure the one they purchased with the best cost performance, inferring that they are rigorous decision-makers in this condition. Although they seldom bought the high-risk product online (due to the concern on delivery or security), they all sought for product information through e-media, especially sites providing consumer reviews, to decide on two to three candidates. Then, they went to real stores to physically evaluate the candidates and make a purchase decision among them. It can be hence seen that the online environment has been at least adopted as an efficient information seeking platform for users to construct product preferences, and social resources (such as product reviews) seem playing an important role in absorbing them to the environment.

D. Procedure

We targeted to collect in-depth information from the samples of consumers to uncover the deeper motives for their product choices. The participant was encouraged to freely use any product features from both Flickr Camera Finder and Yahoo Shopping (as listed in TABLE I) to accomplish the task of: "*Imagine you are prepared to buy a digital camera. Please use the assigned sites to find information and identify the product that meets your needs*". It is worth noting that all of our studied subjects were first-time encounters of the two websites, so they should not be biased by any of previous usages. An initial warm-up period allowed them to familiarize themselves with the sites' facilities as much as possible, so when starting the task, their behavior would be primarily driven by their true information needs. All of their interaction actions, including on-screen mouse moves and inputs, were automatically captured by a screen observer software (i.e., Morae). The analysis of each user's log file can hence tell us what data s/he intentionally processed and when. After her/his choice was made, a post-study questionnaire was to be filled in, requesting the participant's final decision confidence and purchase intention. S/he was also asked of intention to contribute content to the site(s) once revisiting.

IV. RESULTS ANALYSIS

In this section, we show analysis of all users' actions within their whole task performance, with the emphasis on studying their information needs at different processing stages.

A. Consumer Decision Process

As mentioned before, complex design making has been often referred to a two-stage process: initial screening and in-depth evaluation [8, 17]. Tracing our users' actual behavior surprisingly indicates that they all exhibited a more precise three-stage procedure (see Figure 1): 1) to screen all alternatives and select ones for in-depth evaluation; 2) to view the product's details and save it in wish list if near-satisfactory; 3) to compare candidates in the wish list and make the final choice. Moreover, the transition between stages has been found not in a sequential order, but being iterative in nature and the size of consideration set in fact gradually decreases.

Concretely, at the beginning of the decision process, each user was first with some initial preferences in mind. As stated by her/him, the preferences were rough needs in general, such as looking for a camera that is "*easy to use*", "*easy to carry*", *"with colorful images", "of high cost performance"*, "*better for night scenes*", or "*better for long distance picture-taking"*. Six users also had specific criteria on some static parameters (e.g., type, megapixels, screen size, battery, or focal length). As for price, 5 users expressed the need (e.g., "cheap", "not expensive", or "under $500").

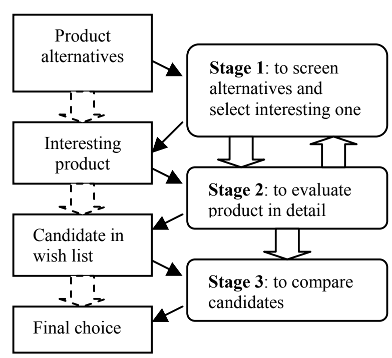

Figure 1. Three-stage consumer decision process with input and output for each stage.

As further observed from their interaction logs, they maximally considered four favorable brand, and the favor was coming from their internal memory about the brand's reputation or based on prior usage experiences, as analyzed from their think-aloud protocols. The information processing was then typically brand-based. That is, they first narrowed down to one brand to seek for its alternatives' basic information (stage 1). If anyone(s) interested them, they went to examine its details and saved it into the wish list if near-satisfying their needs (stage 2). Then, they started over to consider another preferred brand with the similar process. This iterative cycle between stages 1 and 2 continued until a set of candidates was determined. At this point, they entered into stage 3 to compare candidates in the wish list in order to confirm the final choice. Figure 1 concretely illustrates the three-stage consumer decision process (with input and output for each stage), and an example process from a representative user (see Figure 2).

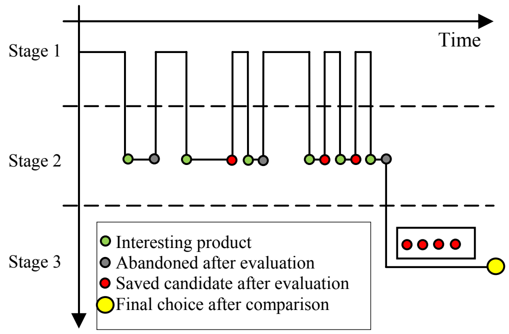

Figure 2. An example decision process of user behavior (along the time dimension).

B. *Information Processing at Different Decision Stages*

It is then interesting to know what product information (e.g., social features) that users have in reality processed at different stages.

Stage 1 (to screen out interesting alternatives). At this stage, we quantitatively measured how many products were selected and from where they were located. It indicates that on average 9.67 (*St.d.* = 4.78) products were chosen to view details, among which 5.42 were located in Yahoo, and 4.25 were in Flickr CF. Figure 3 shows the distribution of their origins. Basic static features provided by Yahoo for browsing/filtering got the highest chance enabling the average user to obtain 39.79% interesting products, and the second and third winners come to Flickr CF's popularity-based sorting list (27.51%) and brand popular products (12.18%). In comparison, Yahoo's popularity list got much less successes (5.28%). In fact, there were only 2 participants who accessed "Top Digital Cameras" in Yahoo, against 9 consulting the popularity ranking in Flickr CF. As said by users, "*Popularity is a suitable proxy to measure the product's quality when I am not familiar with a brand or uncertain about what I want*". It was also regarded as "*the best form of recommendations*" in this condition. Users' reflective thoughts further exposed their inherent propensity to trust the info from the social media site because it is perceived more credible (see the later discussion).

Remaining products were either searched out by keywords (e.g., a pre-known product model) (6.53%), coincidently discovered through Flickr's photo related products (4.83%) or Yahoo's related products (i.e., "*shopper who viewed this also viewed …*", 3.89%).

Therefore, above half of selected products (53.69%) were stemmed from product suggestions based on social features. Especially, popularity-based ones were shown most instrumental compared to other social types at the first decision stage.

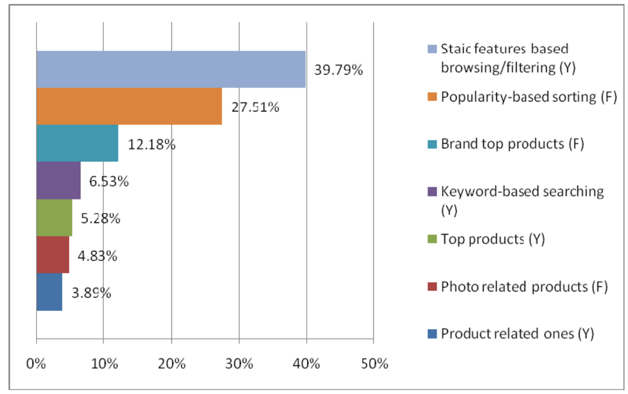

Figure 3. (Stage 1) Intereslting products' origins (Y for Yahoo CF, F for Flickr CF), and their overall distribution in respect of social versus static sources.

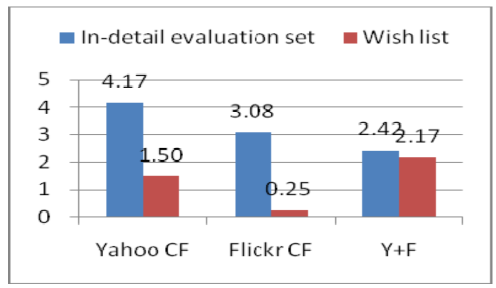

Figure 4. (Stage 2) Product evaluations distributed on site page(s) and number of candidate selections in the wish list.

Stage 2 (to evaluate products in detail). As for what detailed info that users have evaluated for interesting products, the analysis of their page visits indicates that 42.86% of products were evaluated on Yahoo (that provides the product's full specifications, price comparison and user ratings/reviews), 30.44% on Flickr CF (providing the product's usage trend and associated photos), and 26.70% on both sites' product pages. Among the examined products, 45.82% were finally put into the average user's wish list (i.e., 4 products, *St.d.* = 1.95). The page(s) evaluation respectively contributed 39.09% (1.50 products), 6.25% (0.25) and 91.67% (2.17), to establishing the wish list (the % means the percent of products saved as candidates after the corresponding page evaluations, see Figure 4). It hence implies that the combination of product details from both Flickr CF and Yahoo can most likely convince the user to seriously consider the product as a candidate. The correlation is indeed highly significant ($p < 0.001$) by Pearson coefficients. Another fact is that 91.7% (11 out of 12) users' final choice was the product undergoing this combinative review.

Stage 3 (to compare candidates and confirm the final choice). At the last stage when users nearly came to making the "purchase" decision, it was found that they all conducted a more careful comparison among saved candidates in order to confirm the final choice. With the purpose of knowing which factors they mainly considered at this point, we recorded items they viewed after the establishment of their wish lists. It shows that 66.7% (8 out of 12) users went to Flickr CF to either compare candidates' usage trends or photos taken by Flickr community, and 33.3% emphasized product specifications or reviews given in Yahoo (see Figure 5).

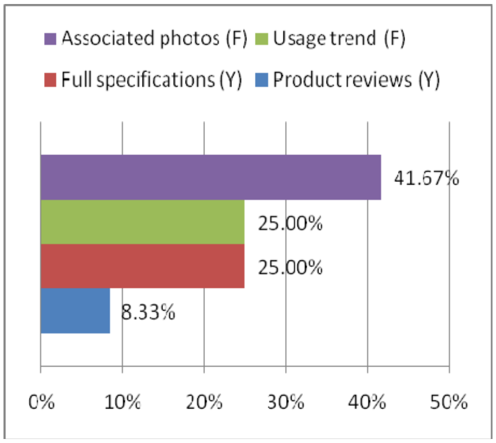

Figure 5. (Stage 3) Considered features in the final stage of product comparison that led to the final choice-making (% of all users) and the features' overall distribution (social vs. static features).

Therefore, as seen from Figure 5, totally 75% of users have lied on social features (i.e., community usage trend, photos, and product reviews) to fulfill the final choice-taking. The social features are hence demonstrated more influential than static product features on convincing users of the "purchase" decision. User comments also reflected that "*I would like to rely on content generated by other consumers to justify which product is better than others*"; "*Images taken with the camera*" (or "*the product's usage trend*") "*can help me better form the correct judgment and reduce the uncertainty from purely evaluating its static specifications*".

C. *Behavioral Intentions*

Decision confidence & Intention to purchase. After the choice-making, post-measurements of users' decision confidence and purchase intention further indicate that most of them (83.3%) were confident that the product they "purchased" is really the best one ($p < 0.01$ by Chi-test). 75% of all users even truly intent to purchase it if given the opportunity ($p < 0.01$ by Chi-test), because "*the chosen product almost matches all of my requirements*" or "*it has the best price quality*". The results thus reveal an overall high level of decision quality that our subjects achieved via using both sites' provided product info (see Figure 6).

Intention to contribute content. How to convince newcomers to become contributors has always been a challenge to social networking sites [2], so another construct we measured during the post-study survey was their intention to contribute content after performing the task (requested to respond on a 5-point Likert scale "*I would like to contribute if returning to the site*" from "strongly disagree" to "strongly agree"). 83.3% users agreed that they would like to contribute items to either Flickr CF, or Yahoo, or both. The average score on Flickr CF was actually higher than on Yahoo CF (mean = 3.75 against 3.33, $p = 0.14$, $t = -1.6$).

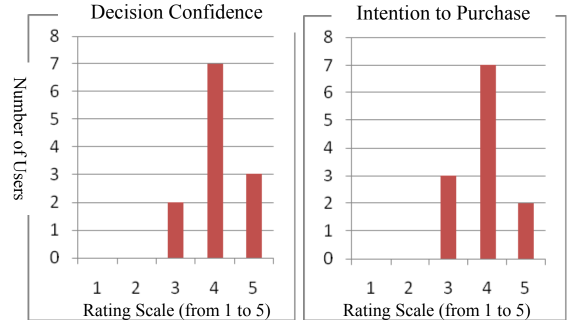

Figure 6. Distribution of numbers of users on the rating schale (from 1 "strongly disagree" to 5 "strongly agree") respectively for **Decision Confidence** ("*I am confident that the product I just 'purchased" is really the best for me*") and **Intention to Purchase** ("*If given the opportunity, I will buy the product I just chose*").

The findings hence interestingly suggest that stimulating users to in practice experience the benefits of social features (e.g., searching for a product based on the info) will likely promote their motivation to contribute, probably with the kindness to serve others with similar task goal. Items that users indicated to share include product ratings, product reviews, responses to other users' reviews, and product photos. The contribution level of each item is significantly different between the two sites ($p = 0.057$ by Chi-test, see Figure 7): users more voluntarily upload photos in Flickr CF, but create product reviews in Yahoo. It hence implies that if a user can in reality taste the merit of a certain social feature provided on the site, s/he will be more motivated to be its contributor.

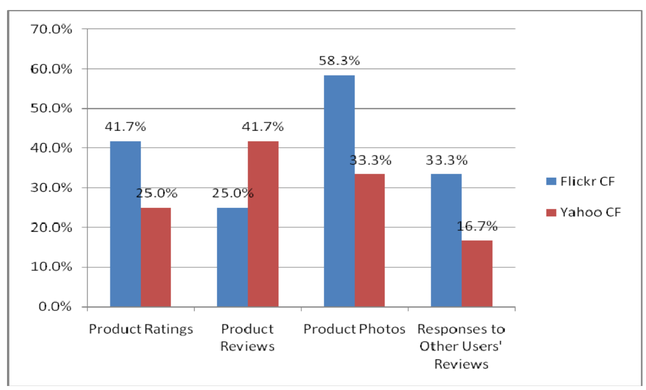

Figure 7. Items that users (in percentage) would like to contribute.

D. *Reflective Comments*

With the doubt that why users went to Flickr CF for accessing "product popularity", when the similar info was also available in Yahoo CF, we asked users this question at the end. They responded that because it was perceived more trustworthy in Flickr CF: "*I trust the information on the social forum*"; "*I trust Flickr's popularity information because of its large amount of users*"; "*Flickr is more neutral and credible*"; "*Although this is my first-time using this website, the information sounds credible since it should be based on actual usages.*" They felt that the way of displaying popular cameras through community members' uploaded photos is interesting and surprising at the first impression. They were soon used to it to refer to the popularity ranking whenever needed. On the contrary, the product popularity on Yahoo Shopping site (e.g., "top Digital Cameras", that also widely appears in other standard e-stores) was commented "*less trustworthy*". Some users indicated that: *"The 'top products' in Yahoo may be only dependent on users' clicks or for companies' promotion purpose."* "*The popularity information in Yahoo may be faked. It looks more trustworthy and real in Flickr.*" *"Flickr is more neutral because it is a consumer-operated website. The information on Yahoo may be not so real because it is more commercial-oriented."* It can be thus seen that users had propensity to trust the data from the social networking platform because it depends on a large community's contributions.

Furthermore, as for the popular recommendations, one user suggested taking geographical distribution into account, such as separating users in Flickr community by their regions so as to distinguish product differences ("*one camera model was sold in Europe, but probably not in China*") and cultural impacts ("*people from the same cultural background may have common behavior*"). Another user proposed to add time dimension to compute product popularity, given that old models would be used by more users. He commented that "*popularity should better be compared between products that were released at the same time.*"

Users also gave comments on another type of product suggestions (i.e., "*shoppers who viewed this product also viewed ...*"). They suggested computing the "related products" according to experts' professional opinions on the relevance of current viewed product with others, rather than just being dependent on other consumers' clicks. As said by one user, "*imagine the friends around you all use Canon, you will not be familiar with Nikon. But if there is a comparison table from an expert explaining what their differences are, I will go to see Nikon's products***.**" Another user also mentioned "*because people sometimes just randomly clicked, the information from 'shopper viewed this product also viewed others' cannot be referential and credible. Experts' suggestions can be more useful to be regarded as important reference.*" Some users also suggested filtering the related products to only list ones with the same price level or product type: "*The 'related products' is useful, but I will not be interested in ones with large price distance." "If it contains products with the same level of price and of similar product type, I will more likely consider them.*" Therefore, it suggests that showing "related products" through detailed comparison based on experts' opinions, and matched to the user's hard constraints (e.g., on price, type), will potentially have more chances to increase their applicability.

Moreover, most of users expressed preference over the separation of reviews in pros and cons categories. Actually, "*the negative reviews are more important than positive ones*"; "*the motivation of buying a product is not because it is so perfect, but is whether you can stand its drawbacks"*; "*every camera should have flaws, and what I want to know from user reviews is whether they can expose these negative aspects*". All participants agreed that they will not buy a product only because it has positive ratings and reviews, but will certainly not buy it if it has negative reviews especially on features that they are most concerned about. Moreover, some users commented that the amount of reviews also takes effect: "*few user reviews have lower credibility*", but it was commented still being better than zero (e.g., "*in the case that two compared products both have few reviews, I will still read them to judge which product would be better*").

V. Design Implications and Conclusion

Thus, by observing users' behavior while searching for a high-value product, we understand how the process was concretely conducted across different stages, and what roles different social features respectively took to assist users in making an informed decision. Concretely, it has been found that *product popularity* performed much actively at the first stage to aid users in the location of interesting products, because users' objectives were generally not clear at the start when facing the high-risk product and they were inclined to consult the popularity ranking. After then, in-depth examination was performed to the interesting product, at which point, the combination of *both static product specifications and social features* (including product ratings/reviews, usage trend and resulting images like photos of the camera) was most effective in convincing the user to consider the product as a candidate. The transition between the two stages (i.e., to select a product, and to in-depth evaluate it) was following an iterative cycle, until a set of candidates was determined. The final stage then came, where users carefully compared the candidates and most of them relied on *social factors* to judge the optimality of one compared to others. As the result, they almost all achieved a high level of decision confidence after freely using the combinative product info (i.e., detailed static product features plus various sorts of social values) from Yahoo and Flickr CF. Most of them even wanted to purchase the chosen product if given the opportunity. Moreover, the majority of users expressed intention to contribute content to the sites once returning, verifying again the working merits of different social features (such as product ratings, reviews, photos, reviews' responses) in their decision experience.

Their qualitative comments further revealed their improving suggestions on the social information presentation. In particular, three enhancements are implied to the current designs: 1) "product popularity" better originates from social media and is based on real usages (as from Flickr) because it will be likely perceived more credible at this platform than in traditional e-stores; 2) "related products" will be potentially more referential if they are integrated with experts' professional suggestions and more personalized in matching to the user's constraints (e.g., on price, type); 3) as for "product reviews", users care more about negative comments than positive ones, so the exposure of related info and the indication of their relevance to user preferences will be likely useful to enable more effective decision.

All in all, according to the exploratory study's results, we believe that at least the two major types of social resources, *product popularity* and *consumer reviews*, can be well integrated into an adaptive decision support to server users when they are at different decision stages. Specifically, the former can primarily assist users when with unclear criteria at the beginning and help to improve user trust in the recommended items if resourcing from social networking media. The latter one, including variations of community usage trends and product photos, should be particularly assisting during the stages of product evaluation and final choice-making, so as to be helpfully combined with static product features to develop more intelligent feature-based decision agents, such as improving tradeoff supports [18] to facilitate users' compensatory comparisons among options. In the future, we will attempt to build a system to embody these implications. We will also conduct large-scale quantitative studies to test the system's adaptive characteristics and practical user benefits. Our ultimate goal is to optimally aiding online buyers in making a confident and accurate purchase decision especially when facing high-value products. We believe that social features should and will perform crucial role to achieve this goal.

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