# Factors Influencing User Motivation for Giving Online Preference Feedback

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**Joost Broekens** and **Alina Pommeranz** and **Pascal Wiggers** and **Catholijn M. Jonker**[1]

**Abstract.** Preference elicitation is important for any computerized system advising users about choices. Recommender systems aim to propose interesting material to users. Therefore, they must first gather user preferences. Negotiation support systems can only give meaningful bidding advice based on users' preferences regarding negotiable issues and interests. In general, the more detail users are willing to give the better the support will be. We investigated how four factors indluence users' willingness to give detail in an online preference elicitation experiment. 18 users rated 60 items (pictures/songs) with 5 levels of detail (from 3-point scale over affective feedback to free text). For each item, users could choose the desired detail level. Our results show that, of the four factors investigated (having an opinion about an item, content type of the item, familiarity with, and ownership of that item), mainly having an opinion about an item makes users give significantly more detailed feedback. Further, users with an opinion about an item use qualitatively rich affective feedback in 30% of the cases. Our findings indicate that adaptive preference elicitation interfaces can conditionally hide and show fine grained feedback providing a simpler interface, whch can be important for smaller interfaces. Further, the fact that 30% of the cases rated with an opinion included affective detail indicates that users are willing to give rich affective feedback when they have an opinion.

## 1 1. INTRODUCTION

Preference elicitation is an important aspect of any computerized system that is supposed to give personalized advice to users about choices of opinion or behavior. Preference elicitation is about extracting a user's opinion about items (e.g., music, pictures, negotiable issues, interests) in such a way that the extracted opinion actually reflects what the user thinks about that item. Common criteria to evaluate such feedback are reliability and validity. The feedback must be reliable: when the user is asked again for feedback on the same or a similar item, one can assume, all else being equal, that the feedback is similar to the earlier feedback. The feedback must be valid: the feedback as extracted and used by the computerized system should reflect the actual opinion of the user; if a user rates a piece of music 4 out of 5 stars, than that should mean the user likes the piece of content more than average but less than perfect, and other items rated 5 or 3 should be liked more and less respectively.

For example, in recommender systems, the aim is to build a user model for the purpose of proposing interesting and novel material to that user. To achieve this, the recommender system must first gather user preferences that reflect actual interest. There are two main approaches: content-based recommendation and collaborative filtering [12]. The content-based approach goes as follows. The system presents a user with the opportunity to give feedback about an item in the form of a rating mechanism (usually stars or values). Based on this feedback (called content-based feedback, as the user directly rates the content), the system can calculate how much the user likes this content. Given a measure of content similarity (e.g., documents containing the same text) the system can then deduce what other content the user would like and recommend this to the user. The collaborative filtering approach roughly works as follows [13]. Subjects give feedback about items. Sometimes the feedback is implicit such as whether or not a user bought a particular item. Differing from the first approach, the system does not assume anything about items (the content) and can therefore not deduce which other items to propose to the user based on item similarity. Instead, an item-item similarity measure is deduced from a person-person similarity measure, e.g., by analyzing in how far two different users are alike with respect to the items they bought or viewed. In any case, whenever user feedback is used, preference elicitation becomes an issue because the system wants to capture actual interest (or likes and dislikes) to build a user model. For a recent review from the perspective of preference elicitation see [22].

The same holds for negotiation support [23]. If a negotiation support system is supposed to give personalized advice about bids that is meaningful and useful to the user, the system must first extract that user's preferences to build a user model representing the user's possible issues, interests and options involved in the negotiation. When the system knows how important these issues and preferences are to that user, it can start calculating bids that match the user and the opponent best in the negotiation; for example, bids that try to maximize a pareto optimum [16].

In this paper, we address a third issue with respect to preference elicitation, beside validity and reliability: the level of detail of the feedback. In general, the more detail a user is willing to give, the better the bidding support or recommendation will work (assuming it is also valid and reliable). However, one does not want to bother users with an endless interface measuring all kinds of opinions and ratings about items such as persons, songs, pictures, bids, or issues. User motivation is an important aspect to consider when developing systems that need user feedback. For example, when collecting user tags (labels users associate to content items), it is important to consider why users tag the content, for example, to portray themselves, to help categorize the content or to help others find content [1][18]. Ideally a system should motivate users to give feedback, for instance by making the feedback system socially relevant or fun to use [11]. In our work, we took a slightly different approach. We wanted to know how a user's default motivation for giving feedback varies un-

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der the influence of different variables in a relatively neutral setting. With neutral setting we mean that we did not specifically motivate people to give preference feedback by making the system fun, social or otherwise rewarding. It is important to know this default motivation regarding the detail level for at least three reasons. First, up until now there is no such thing as a baseline level of detail users are willing to give as feedback. From a research point of view this is important to have as it allows comparison of different methods to elicit user feedback. Second, if this default motivation varies depending on the user, the type of content or other variables, then it is worthwhile to adaptively give a user the opportunity to add more detail based on these variables. Doing so will increase the level of detail of the extracted preference and hence increase the amount of available information for subsequent user modeling, without bothering the user because the user's intrinsic motivation already triggers him or her to give more detail. Third, most preference feedback is given by means of 5-point Likert scales. Affective feedback is currently being investigated as an additional way of asking feedback. This is being tested in different domains, such as interactive television [14] and music annotation and retrieval [17]. Such studies show that adding affective information indeed can be beneficial to user models. The question is however, do users want to give additional levels of affective feedback, and how far do they go in giving detail?

We investigate the following hypothesis: the level of detail persons are willing to give in their feedback depends on content type, familiarity, ownership and opinion. To be more precise: when users are free to choose the level of detail they want to give about a particular piece of content, how far would they go in giving feedback, and does this depend on the content type, whether they own or are familiar with the content and whether they have an opinion about the content. We present results of an online experiment in which 18 users rated 60 items (30 pictures of well-known persons, 30 popular songs) with 5 different levels of detail: 3-point scale, 5-point likert scale, affective feedback using the *AffectButton* [3], emotion words and free text feedback. For each item, the user chose the desired level of detail. Our results show that the main factor influencing the amount of detail users are willing to give is whether or not they have an opinion about the item at all, while content type, familiarity with, and ownership of item did not have an important influence. Further, users with an opinion include affective (emotional) feedback in their feedback.

## 2 RELATED WORK

People's preferences have been the interest of researchers in many different fields. These include psychology, behavioral science, consumer research, e-commerce, recommender systems as well as negotiation and decision support. In the introduction to our work we mentioned the importance of preference elicitation for computerized support systems, such as recommender systems or negotiation support systems. In this section we dig deeper into related work in the area of preference elicitation interfaces. First, however, we give a short overview of studies from psychology and behavioral sciences that focus on how people come to have preferences.

### 2.1 Constructed Preferences

Carenini and Poole [6] describe two very influential conceptual shifts for classical decision theory: constructive preferences [21] and value-focused thinking [16], and their implications for preference elicitation. We will focus here on the first shift which has occurred in behavioral decision making. Many studies have confirmed that preferences are not stable but constructive. This means that people do not have well-defined preferences in most situations but rather construct them when necessary, i.e., in the decision making context. There are different views on how people construct their preferences. Simon et al. [29] for instance found in their experiments that while people processed the decision task, their preferences of attributes in the option that was chosen increased whereas those for attributes of rejected options decreased. Similar effects have been found in negotiation settings reported by [8]. It is also in line with Bettman and Luce's [2] idea of trying to maximize the ease of justifying a decision while making it. Another aspect of constructing preferences has been brought forward by [10] focusing on the goals of the decision task in relation to a so-called prominence effect. This effect occurs when people prefer an alternative that is superior only on the most prominent, i.e. the most important, attribute. They confirmed in three studies that the prominent attribute will be more heavily weighted when the goal was making a choice between alternatives than when the goal was to arrive at a matching value.

The research above implies that we have to think carefully about the way we pose a preference elicitation task to our users, in order to avoid unwanted effects. Another view on constructing preferences comes from [30] and states that people construct preferences from memory. The authors present the so-called PAM (preferences-as-memory) framework, which assumes that "decisions (or valuation judgments) are made by retrieving relevant knowledge (attitudes, attributes, previous preferences, episodes, or events) from memory in order to determine the best (or a good) action." They also emphasize that this is not an entirely cognitive view on preference construction since affect determines what the person recalls first. Information consistent with emotions is more available in memory. For our study this is interesting for two reasons: (1) if people construct preferences based on their memories, familiarity of an item might influence the detail of the given preference and (2) if emotional factors play a role in the construction of preferences, then how likely are people to use affective feedback methods.

Other psychological effects have been found when people construct their preferences. For example, anchoring effects and effects that occur when complicated numbers or information are presented in the choice task [15]. Different ways to measure preferences can lead to different results, which is usually not the intention of eliciting preferences. To help people to construct their preferences in health care scenarios, Johnson and colleagues [15] suggest to present default choices that have lead to the best outcome for most patients and present information in a way that helps the patient to understand the outcomes of each choice.

Consumer research looked at the interplay between affect and cognition on decision making [28]. They investigated the influence of available processing resources when confronted with a decision task. In cases people have only few resources available affective reactions tend to have a greater impact on choice, whereas with high availability of resources cognitions related to the consequences of the choice are more dominant. They noted that this finding is influenced also by personality and by the representation of the choice alternatives. Other interesting insights from this research area come from [31] looking at affective and cognitive factors in preferences. Among other things they report that mere exposure of a stimulus can positively influence a person's preference for this stimulus. Conscious recognition, however, was not the dominant factor since people were generally not aware that they had seen the same stimulus earlier.

Concluding this section, we can record that there are many factors influencing preference elicitation. Payne and coworkers [20] have made an attempt to develop guidelines for measuring preferences taking people's behavior into account. Similar work focusing on the user side has been presented in [24] and [25]. Our work is complementary in the sense that we study how four factors, item content type, familiarity with, opinion about, and item ownership influence the level of *preference detail users are willing* to give.

### 2.2 Preference Elicitation Interfaces

Most literature on preference elicitation interfaces focuses on the technical implementations and underlying formal structures instead of on the user input itself. Therefore, it is often not clear how a method facilitates the user to construct preferences. In addition, many systems are based on quantitative methods using utility functions that require special input and assume stable preferences. As the previous section shows, this view is debatable, since people construct their preferences and this construction has many influential factors that need to be carefully considered when designing an interface. We now review several preference elicitation interface approaches. For a recent more detailed review see [22].

Chen and Pu [7] give an overview over existing systems that elicit user preferences. They mention different techniques used in the systems, like knowledge-based find-me techniques [4], example critiquing and tweaking [9], active decisions and clustering or collaborative filtering techniques [26]. There are also hybrid systems combining different approaches [5]. In knowledge-based systems, preferences are elicited by example-similarity; the user rates a given item and requests similar items. Tweaking can be used to limit the similar items to only those satisfying the tweak. In example-critiquing approaches the user is presented with a set of candidates that can be critiqued. The user can either choose one of them or critique some of their attributes. An interesting interface has been developed by [27] called the Apt Decision Agent. In this system people initially provide a small number of criteria for an apartment. Based on those they get a number of sample apartments. They can react to any attributes of any apartment. Interesting here is that the preference feedback by the user gets more and more detailed during the interaction. At the same time the user is not *forced* to go into more detail, but is free to give only the feedback the user wants to give. A similar approach is called Active Decisions and used in many online shopping environments, where people go through a two stage process. First, they screen a large set of products from which they choose a promising subset. Second, they evaluate these in further detail.

As already mentioned, most approaches are focused on techniques to implement the preference elicitation process. Less attention has been given to concrete interface elements used in these approaches and in particular the question 'how much detail a user wants to give using these interface elements". Most approaches assume users that want to interact with the interface and give ratings or critique examples.

## 3 EXPERIMENTAL SETUP

As mentioned in the previous section, most research in preference elicitation pays little attention to the motivation that drives people to enter their preferences into a system and how much detail they are willing to give for each preference. We investigate the hypothesis that the level of detail persons are willing to give in their feedback depends on content type of the item, familiarity with the item, ownership of the item and opinion about the item. We have set up a content rating experiment with content type, ownership and opinion as independent variables and detail as dependent variable. The content was preselected by the experimenters (see Materials and Procedure), and subjects could indicate their familiarity with the content, ownership of, and opinion about each content item. As we had no control over these three variables, we could not do a real 2x2x2 setup: some of the cells in the experiment design would have been (and indeed are) almost empty. As such we will consider the three variables as independent factors (we will not test for dependencies). For the influence of familiarity on detail a standard correlation study was performed, based on the same data, with familiarity as independent variable and level of detail as dependent variable.

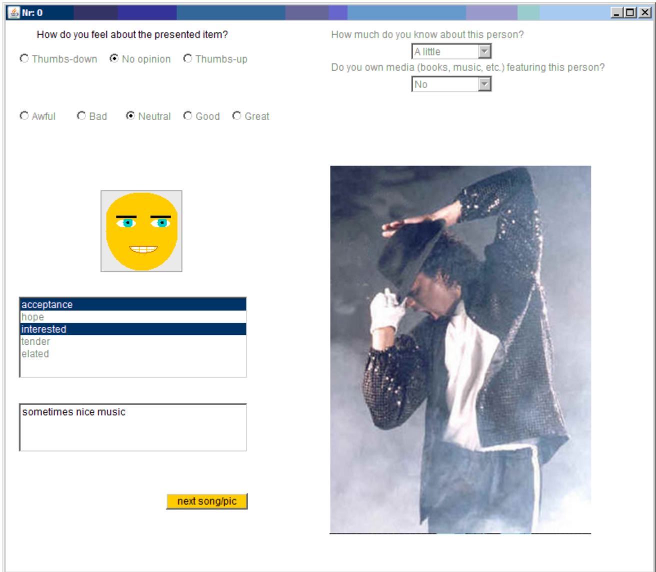


**Figure 1.** Example of the interface for testing the level of detail. In this figure the levels are all shown on the left side of the screen. From top to bottom: 3-point, 5-point, AffectButton, emotion words and free text. On the right side the current stimulus and the fields to fill in familiarity and ownership. In this figure, all levels are shown, but during the experiment a subject sees a level only when he/she pressed the "DETAIL" button situated next to the "next song/pic" button (not shown here, because all levels have been filled in).

### 3.1 Participants

We selected participants from a broad range of people that indicated earlier that they would like to take part in experiments. We tested 18 participants, 12 male and 6 female between the age of 21 and 65 (avg=30, stdev=10). Participants have different cultural backgrounds as well as nationality and education.

### 3.2 Material and Procedure

Participants received an email with the invitation to participate including a link to the application needed for the study. The study was done online, so subjects did the experiment at a place of their own choice when they wanted. The participants were told that the experiment was about creating an alternative top-40 of famous people and popular music. The real goal of the experiment was kept secret, so that user motivation was not influenced by the instructions. The email contained detailed instructions about how to use the application. After the participants started the application, they were asked to fill in some standard information (age, gender, and education). After filling in this information, they were presented with 30 songs and 30 pictures of famous people (one at the time, at random). For each picture/song they were asked to fill in their familiarity with the song or person (5-point scale) and whether or not they owned the song or media concerning the person (yes/no) (see right side of the window in Figure 1). Then they were asked to give their opinion about the picture/song. For each stimulus they had to give at least a thumbs-down/neutral/thumbs-up opinion (3-point scale). Neutral was interpreted as no opinion, thumbs-down and thumbs-up were interpreted as having an opinion. After that, they had the choice to enter more detail to their opinion (click on a button: DETAIL) or go to the next picture/song (click on a button: next song/pic). The position of the two buttons was randomly interchanged for each new content item to avoid a bias for clicking one or the other. There were 5 levels of detail and each level had to be filled in before the participant could go to the next to make sure the user takes an active decision in whether to give more feedback or not. However, at every level subjects could stop giving feedback and go to the next stimulus, except at the obligatory first level. With these levels we wanted to test (a) for more detail with respect to granularity (level 1 - level 2), and (b) more detail with respect to additional affective dimensions (level 2- level 3). Free labels (level 4) were added to add expressive power to level 3. Free text input (level 5) was added to give the user full expressive freedom. The levels are:

1. Thumbs-down/no opinion/thumbs-up. All subjects had to rate their opinion about each item using this input level.
2. A 5-point scale ranging from awful to great. This was a more detailed version of the first level, introducing 5 options: Awful, Bad, Neutral, Good, Great.
3. Affective feedback using the AffectButton, an interactive button that can be used to give affective (emotional) feedback based on three dimensions: pleasure, arousal and dominance [19]. It is a dynamically changing selectable emotion expression. The expression changes based on the position of the mouse in the button. Previous research has shown that the AffectButton is useable and produces reliable and valid affective feedback [3].
4. Emotion words that match the feedback filled-in with the AffectButton. Based on a subject's feedback for an item at level 3, five emotion words out of a total of 31 were presented that best matched the feedback. The complete list of words spanned the pleasure-arousal-dominance space. If a user entered a happy face, words such as happy, content, etc. would be presented in the option list.
5. Free text input. This option enables subjects to give free text input about an item as a last level of detail.

All data were collected at a central server including the actual level of detail (1-5) entered per item. We took each rated item as statistical unit of analysis resulting in a total of 18*60=1080 cases. Excel and StatistiXL were used to analyze the data.

# 4 RESULTS AND DISCUSSION

Before analyzing the data related to our hypotheses, we first did several checks to find out if the experiment went as intended. The correlation between sequence number of item presented and detail was not significant, indicating that there were no wear or boredom effects on the subjects during the course of the experiment. Correlations between level-1 (thumbs), level-2 (5-point) and the continuous pleasure scale of level-3 (AffectButton) were all high and significant (all $r > 0.8$, sign. $< 0.001$), as would be expected. This indicates subjects are consistent in their ratings and therefore we can assume subjects participated seriously in the experiment.

## 4.1 Opinion influences amount of feedback

With regards to our hypotheses, we found a significant, but not very large, influence of content type and ownership on the level of detail subjects would enter for an item. Music is rated with more detail ($meanlevelofdetail = 2.0$) than pictures of famous people ($mean = 1.8; F(1, 1078) = 5,3; p = 0.02$). Items owned by a person are rated with more detail ($mean = 2.2$) than items not owned ($mean = 1.9; F(1, 1078) = 8.1; p < 0.01$). We found a significant and large influence of opinion on the level of detail entered. Items about which a person has an opinion are rated with much more detail ($mean = 2.1$) than items about which a person has no opinion ($mean = 1.4; F(1, 1078) = 65; p = 0$). In fact, in a backwards stepwise linear regression analysis (to check which of these factors has what responsibility for the variation in the level of detail), only opinion came out as a significant model for predicting the level of detail. These results tell us that people who have an opinion about something feel the need to give more detailed feedback about that item. This influence has been found for both content types, and there was only a small interaction effect between content type and opinion ($2x2ANOVA, F(1) = 4.5; p = 0.03$). The regression and ANOVA analyses indicate that, for practical purposes, of the four factors investigated, the user's opinion using a 3-point feedback scale is the important factor that influences the amount of feedback given.

With regards to the effects of familiarity we found an interesting pattern that depends on opinion. Familiarity was correlated positively with level of detail when taking all cases into account ($n = 1080; p < 0.001; r = 0.136$); however, the correlation is rather small. When we repeated the analysis with only those cases where a subject used at least the 5-point scale (level 2) the correlation disappeared. However, when we again repeated the analysis but now with only the cases where a subject used at least the affective feedback (level 3), the correlation was negative and much stronger ($n = 262; p < 0.001; r = -0.353$). This indicates a nonlinear relationship between familiarity and level of detail. It seems that in general familiarity with the item does not play a major role in the level of detail one wants to give as feedback, unless one has an opinion about the item and one is unfamiliar with the item. In that case, subjects used more detail to express their opinion.

## 4.2 Affective feedback used to express opinion

To gain a little more insight into the distribution of the use of feedback detail, consider Figure 2. Of all cases rated as ”no-opinion”, only about 22% will subsequently be scored using more detail than a three point thumbs-up/no opinion/thumbs down scale. Only in about $11\%$ of those cases affective feedback is used. In contrast, if a case is rated as ”thumbs-up” or ”thumbs-down”, these figures change dramatically. Now, $48\%$ of the cases are rated using a 5-point scale and $31\%$ of the items are rated using affective feedback.

## 4.3 Discussion of relevance

Our results clearly show that the amount of feedback detail, including affective feedback, strongly depends on whether users have an opinion. This is in itself not very surprising, but it is relevant for several reasons. *First*, the results show that an adaptive preference elicitation interface can take into account course grained feedback for predicting if fine grained feedback is needed. This means that the interface can conditionally hide and show the fine grained feedback providing a simpler interface. This can be particularly important for smaller interfaces, such as those used for mobile devices. *Second*, the results show that users are willing to give affective feedback when they have an opinion. Affective feedback is qualitatively richer data than standard one-dimensional feedback and is therefore important to consider in preference elicitation interfaces. *Third*, our results give a first baseline of the amount of feedback that can be expected given that no effort has been done to motivate the user to give feedback (e.g., using social computing, added functionality). As we did not prime subjects to give any level of detail (for each item a user explicitly indicated by pushing a button the need for the next level), and as the type of content only marginally influences the amount of feedback given, our results seem valid as "baseline motivation". *Fourth*, future work is needed to investigate the exact influence of familiarity on the amount of detail given, as the influence of this factor seems to be dependent on opinion.

Of course our findings are limited. They relate to online, web-based, preference elicitation, and our experiment should be repeated in other domains, with larger groups of users, and different rating tasks, goals and contexts.

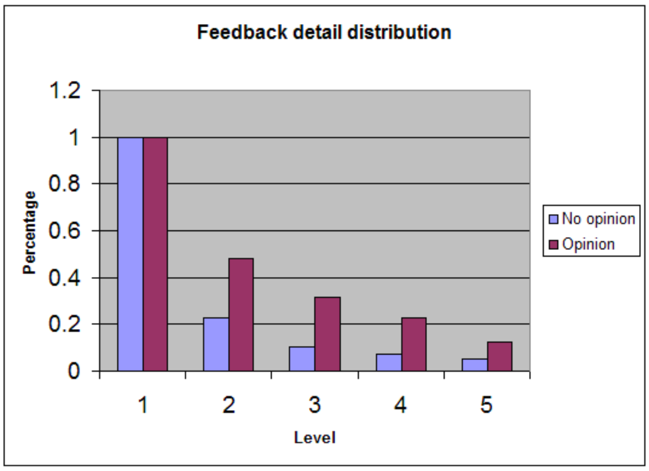


**Figure 2.** The figure shows the distribution of the levels of feedback given for all cases. Level 1 was always given (see experiment setup). For example, 48% of the people used the 5-point Likert scale when they had an opinion, while only 22% used it when they did not have an opinion.

## 5 CONCLUSIONS

We have argued that it is important to consider the level of detail a user is willing to give when asked for feedback about a content item. We have done a web-based preference elicitation experiment testing the influence of four factors on the amount of detail given. The four factors investigated are type of content, familiarity with the content, ownership of the content and, whether or not a subject has an opinion about the content. Opinion showed to be the most important factor. Subjects with an opinion about an item gave significantly more detail than when an opinion was absent. This provides opportunities for adaptive preference elicitation interfaces to conditionally hide and show fine grained feedback providing a simpler interface, whch can be important for smaller interfaces. Further, 30% of the cases rated with an opinion included affective detail, indicating users' willingness to give rich affective feedback when they have an opinion.

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## REFERENCES

[1] Morgan Ames and Mor Naaman, 'Why we tag: motivations for annotation in mobile and online media', in *Proceedings of the SIGCHI conference on Human factors in computing systems*, pp. 971–980, San Jose, California, USA, (2007). ACM.

[2] James R. Bettman, Mary F. Luce, and John W. Payne, 'Constructive consumer choice processes', *Journal of Consumer Research*, **25**(3), 187–217, (1998).

[3] Joost Broekens and Willem-Paul Brinkman, 'Affectbutton: Towards a standard for dynamic affective user feedback', in *ACII 2009*. IEEE, (2009).

[4] R. Burke, 'Knowledge-based recommender systems', *In A. Kent (ed.), Encyclopedia of Library and Information Systems*, **69**(Supplement 32), (2000).

[5] R. Burke, 'Hybrid recommender systems: Survey and experiments', *User Modeling and User-Adapted Interaction*, **12**(4), 331–370, (2002).

[6] G. Carenini and D. Poole, 'Constructed preferences and value-focused thinking: Implications for ai research on preference elicitation', in *AAAI-02 Workshop on Preferences in AI and CP: symbolic approaches*, Edmonton, Canada, (2002).

[7] L. Chen and P. Pu, 'Survey of preference elicitation methods', Technical report, Swiss Federal Institute of Technology in Lausanne (EPFL), (2004).

[8] Jared R. Curhan, Margaret A. Neale, and Lee Ross, 'Dynamic valuation: Preference changes in the context of face-to-face negotiation', *Journal of Experimental Social Psychology*, **40**(2), 142–151, (2004).

[9] B. Faltings, P. Pu, and M. Torrens, 'Designing example-critquing interaction', in *IUI*, Portugal, (2004). ACM.

[10] Gregory W. Fischer, Ziv Carmon, Dan Ariely, and Gal Zauberman, 'Goal-based construction of preferences: Task goals and the prominence effect', *Management Science*, **45**(8), 1057–1075, (1999).

[11] Jenneke Fokker, Huib de Ridder, Piet Westendorp, and Johan Pouwelse, 'Psychological backgrounds for inducing cooperation in peer-to-peer television', in *Interactive TV: a Shared Experience*, pp. 136–145, (2007).

[12] David Goldberg, David Nichols, Brian M. Oki, and Douglas Terry, 'Using collaborative filtering to weave an information tapestry', *Commun. ACM*, **35**(12), 61–70, (1992).

[13] Jonathan L. Herlocker, Joseph A. Konstan, Loren G. Terveen, and John T. Riedl, 'Evaluating collaborative filtering recommender systems', *ACM Trans. Inf. Syst.*, **22**(1), 5–53, (2004).

[14] Shang Hsu, Ming-Hui Wen, Hsin-Chieh Lin, Chun-Chia Lee, and Chia-Hoang Lee, 'Aimed- a personalized tv recommendation system', in *Interactive TV: a Shared Experience*, pp. 166–174, (2007).

[15] E.J. Johnson, M. Steffel, and D.G. Goldstein, 'Making better decisions: From measuring to constructing preferences', *Health Psychology*, **24**(4), S17–S22, (2005).

[16] R. Keeney and H. Raiffa, *Decisions with multiple objectives: preferences and value tradeoffs*, Cambridge University Press, Cambridge, 1993.

[17] Micheline Lesaffre, Marc Leman, and Jean-Pierre Martens, 'A user-oriented approach to music information retrieval', in *Dagstuhl Seminar Proceedings 06171*, (2006).

[18] Cameron Marlow, Mor Naaman, Danah Boyd, and Marc Davis, 'Ht06, tagging paper, taxonomy, flickr, academic article, to read', in *Proceedings of the seventeenth conference on Hypertext and hypermedia*, pp. 31–40, Odense, Denmark, (2006). ACM.

[19] A. Mehrabian, *Basic Dimensions for a General Psychological Theory*, OG&H Publishers, 1980.

[20] John W. Payne, James R. Bettman, and David A. Schkade, 'Measuring constructed preferences: Towards a building code', *Journal of Risk and Uncertainty*, **19**(1), 243–270, (1999).

[21] J.W. Payne, J.R. Bettman, and E. J. Johnson, *The Adaptive Decision Maker*, Cambridge University Press, 1993.

[22] Bart Peintner, Paolo Viappiani, and Neil Yorke-Smith, 'Preferences in interactive systems: Technical challenges and case studies', *2009*, **29**(4), 13–24, (2009).
[23] A. Pommeranz, W-P Brinkman, P. Wiggers, Joost Broekens, and Catholijn M. Jonker, 'Design guidelines for negotiation support systems: An expert perspective using scenarios', in *ECCE 2009*. ACM, (2009).
[24] P. Pu, B. Faltings, and M. Torrens, 'User-involved preference elicitation', in *In IJCAI-03 Workshop on Configuration*, (2003).
[25] Pearl Pu and Li Chen, 'User-involved preference elicitation for product search and recommender systems', *AI Magazine*, **29**(4), 93–103, (2009).
[26] A.M. Rashid, I. Albert, D. Cosley, S.K. Lam, S.M. McNee, J.A. Konstan, and J. Riedl, 'Getting to know you: Learning new user preferences in recommender systems', in *IUI*, San Francisco, California, (2002). ACM.
[27] S. Shearin and H. Lieberman, 'Intelligent profiling by example', in *Proceedings of the 6th international conference on Intelligent user interfaces*, pp. 145–151, Santa Fe, New Mexico, United States, (2001). ACM.
[28] Baba Shiv and Alexander Fedorikhin, 'Heart and mind in conflict: The interplay of affect and cognition in consumer decision making', *Journal of Consumer Research: An Interdisciplinary Quarterly*, **26**(3), 278–92, (1999).
[29] D. Simon, D. C. Krawczyk, and K. J. Holyoak, 'Construction of preferences by constraint satisfaction', *Psychological Science*, **15**, 331–336, (2004).
[30] E. U. Weber and E. J. Johnson, 'Constructing preferences from memory', in *The Construction of Preference*, eds., S. Lichtenstein and P Slovic, pp. 397–410, New York, NY, (2006). Cambridge University Press.
[31] Robert B. Zajonc and Hazel Markus, 'Affective and cognitive factors in preferences', *Journal of Consumer Research*, **9**(2), 123, (1982).