10
Online consumer decision making

10.1 Introduction

Customers who are searching for adequate products and services in bricks-and-mortar stores are supported by human sales experts throughout the entire process, from preference construction to product selection. In online sales scenarios, such an advisory support is given by different types of recommender systems (Häubl and Murray 2006, Xiao and Benbasat 2007). These systems increasingly take over the role of a profitable marketing instrument, which can help to increase a company's turnover because of intelligent product and service placements. Users of online sales environments have long been identified as a market segment, and the understanding of their purchasing behavior is of high importance for companies (Jarvenpaa and Todd 1996, Thompson and Yeong 2003, Torkzadeh and Dhillon 2002). This purchasing behavior can be explained by different models of human decision making (Gigerenzer 2007, Payne et al. 1993, Simon 1955); we discuss selected models in the following sections.

Traditional models of human decision making are based on the assumption that consumers are making optimal decisions on the basis of rational thinking (Grether and Plott 1979, McFadden 1999). In those models, consumers would make the optimal decision on the basis of a formal evaluation process. One major assumption is that preferences remain consistent and unchangeable. In contradiction to those economic models, research has clearly pointed out that preference stability in decision processes does not exist. For instance, a customer who purchases a digital camera could first define a strict upper limit for the price of the camera, but because of additional technical information about the camera, the customer could change his or her mind and significantly increase the upper limit of the price. This simple example clearly indicates the nonexistence of stable preferences, which led to the development of different alternative decision models (Gigerenzer 2007, Payne et al. 1993, Simon 1955). The most important models are discussed here.

Effort accuracy framework. This model focuses on cost-benefit aspects, in which a decision process is interpreted as a tradeoff between the decision-making effort and the accuracy of the resulting decision. It is based on the idea that human decision behavior is adaptive (Payne et al. 1993) and that consumers dispose of a number of different decision heuristics that they apply in different decision contexts. The selection of a heuristic depends on the decision context, specifically on the tradeoff between decision quality (accuracy) and related cognitive efforts. The effort accuracy framework clearly contradicts the aforementioned economic models of decision making, in which optimality aspects are predominant and cognitive efforts in decision processes are neglected. The quality of consumer decision support in terms of perceived usefulness and ease of use has an important impact on a consumer's behavioral intentions – for example, in terms of reusing the recommender system in the future. Explanations regarding the interdependencies between usefulness and usability factors and behavioral intentions are included in the so-called technology acceptance model (TAM); for a related discussion see, for example, Xiao and Benbasat (2007).

Preference construction. The idea of interpreting consumer choice processes in the light of preference construction has been developed by Bettman et al. (1998). Their work takes into account the fact that consumers are not able to clearly identify and declare their preferences before starting a decision process – decision making is more characterized by a process of preference construction than a process of preference elicitation, which is still the predominant interpretation of many recommender applications. As a consequence of these findings, the way in which a recommender application presents itself to the user has a major impact on the outcome of a decision process.

To make recommenders even more successful, we must integrate technical designs for recommender applications with the deep knowledge about human decision-making processes. In this chapter, we analyze existing theories of decision, cognitive, personal, and social psychology with respect to their impacts on preference construction processes. An overview of those psychological theories and their role in recommender systems is given in Tables 10.1 and 10.2. Table 10.1 enumerates cognitive and decision psychological phenomena that have a major impact on the outcome of decision processes but are not explicitly taken into account in existing recommender systems. Table 10.2 enumerates

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Table 10.1. *Theories from cognition and decision psychology.*

Theory	Description
Context effects	Additional irrelevant (inferior) items in an item set significantly influence the selection behavior.
Primacy/recency effects	Items at the beginning and the end of a list are analyzed significantly more often than items in the middle of a list.
Framing effects	The way in which different decision alternatives are presented influences the final decision taken.
Priming	If specific decision properties are made more available in memory, this influences a consumer's item evaluations.
Defaults	Preset options bias the decision process.

relevant phenomena from personality and social psychology that also play a role in the construction of recommender applications. All these theories will be discussed and analyzed in the following subsections.

10.2 Context effects

The way in which we present different item sets to a consumer can have an enormous impact on the outcome of the overall decision process. A decision

Table 10.2. *Theories from personality and social psychology.*

Theory	Description
Internal vs. external LOC	Externally influenced users need more guidance; internally controlled users want to actively and selectively search for additional information.
Need for closure	Describes the individual pursuit of making a decision as soon as possible
Maximizer vs. satisficer	Maximizers try to find an optimal solution; satisficers search for solutions that fulfill their basic requirements.
Conformity	A person's behavior, attitudes, and beliefs are influenced by other people.
Trust	A person's behavioral intention is related to factors such as the willingness to buy.
Emotions	Mental states triggered by an event of importance for a person
Persuasion	Changing attitudes or behaviors

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Table 10.3. *Asymmetric dominance effect.*

Product	A	B	D
price per month	30	20	35
download limit	10GB	6GB	9GB

is always made depending on the context in which item alternatives are presented. Such context effects have been intensively investigated, for example, by Huber et al. (1982), Simonson and Tversky (1992), and Yoon and Simonson (2008). In the following sections we present different types of context effects and then show how these context effects can influence decision behavior in recommendation sessions. The important thing to note about context effects is that additions of completely inferior item alternatives can trigger significant changes in choice behaviors; this result provides strong evidence against traditional economic choice models that focus on optimal decisions. Superiority and inferiority of items are measured by comparing the underlying item properties. For example, in Table 10.3, item A dominates item D in both aspects (price per month and download limit).

Compromise effect. Table 10.4 depicts an example of the *compromise effect*. In this scenario, the addition of alternative D (the decoy alternative) increases the attractiveness of alternative A because, compared with product D, A has only a slightly lower download limit but a significantly lower price. Thus A appears to be a compromise between the product alternatives B and D. If we assume that the selection probability for A out of the set $\{A, B\}$ is equal to the selection probability of B out of $\{A, B\}$, – that is, $P(A, \{A, B\}) = P(B, \{A, B\})$ – then the inclusion of an additional product D causes a preference shift toward A: $P(A, \{A, B, D\}) > P(B, \{A, B, D\})$. In this context, product D is a so-called decoy product, which represents a solution alternative with the lowest attractiveness.

Table 10.4. *Compromise effect.*

Product	A	B	D
price per month	30	25	50
download limit	10GB	3GB	12GB

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Table 10.5. *Attraction effect.*

Product	A	B	D
price per month	30	250	28
download limit	10GB	36GB	7GB

Asymmetric dominance effect. Another type of context effect is *asymmetric dominance* (see Table 10.4): in this case, product A dominates D in both dimensions (price and download limit), whereas product B dominates alternative D in only one dimension (price). In this case, the additional inclusion of D into the choice set could trigger an increase of the selection probability of A.

Attraction effect. Finally, the *attraction effect* occurs in situations in which product A is a little bit more expensive but of significantly higher quality than D (see Table 10.5). In this situation as well, the introduction of product D would induce an increased selection probability for A.

Table 10.6 summarizes the major properties of the context effects we have discussed so far. These effects can be exploited for different purposes within the scope of recommendation sessions:

- *Increased selection share of a target product.* As already mentioned, the selection probabilities change in the case that additional (inferior) items are added to a result set. This effect has been shown in empirical studies in a number of application domains such as *financial services*, *e-tourism*, or *consumer electronics*.
- *Increased confidence in a decision*: context effects in recommendation result sets can not only increase the selection probability for target items (also with more than two items in result set) but also increase a consumer's confidence in her own decision.
- *Increased willingness to buy*: decision confidence is strongly correlated with the willingness to buy (Chen and Pu 2005). Consequently, on the basis of an increased decision confidence, context effects can be exploited for increasing the purchase probability.

From a theoretical point of view these results are important, but the question remains how to really exploit those effects in recommendation scenarios. To predict selection behavior on a recommender result page, we must calculate dominance relationships among different item alternatives. Models for the prediction of item dominances have been introduced, for example, by Teppan

Table 10.6. *Summary of context effects: A is the target item, B represents the competitor, and D is the decoy item.*

Effect	Description
Compromise effect	Product A is of slightly lower quality but has a significantly lower price.
Asymmetric dominance effect	Product A dominates D in both dimensions (product B does not).
Attraction effect	Product A is a little more expensive but has a significantly higher quality.

and Felfernig (2009a) and Roe et al. (2001). The major outcome of those models are dominance relationships between the items of a consideration set (*CSet*).

Formula 10.1[1] allows the calculation of a dominance value for an item x in the item set *CSet*: $d(x, CSet)$. This value is calculated by a pairwise comparison of the item property values of x with each y in *CSet*. When we apply Formula 10.1 to the item set depicted in Table 10.4, we receive the dominance values that are depicted in Table 10.7. For example, item B is better than item A regarding the property *price*; if we interpret $x = A$, then the corresponding dominance value for the property *price* is -0.67 (the factor is negative if the value of x is worse than the value of y). These values provide an estimation of how dominant an item x appears in *CSet*. The values in Table 10.7 clearly show the dominance of item A over the items B and D; furthermore, D is dominated by the other alternatives.

$$d(x, CSet) = \sum_{y \in CSet - x} \sum_{a \in properties} \frac{x_a - y_a}{a_{max} - a_{min}} \tag{10.1}$$

Such dominance relationships can be exploited for configuring result sets (Felfernig et al. 2008c). If a recommendation session results, for example, in $n = 10$ possible items (the *candidate items*, or *consideration set*) and a company wants to increase the sales of specific items (the *target items*) in this set, this can be achieved by an optimal result set configuration that is a subset of the items (e.g., five items) retrieved by the recommender system. The optimization criterion in this context is to maximize the dominance values for the target items.

A further potential application of the aforementioned dominance model is the automated detection of context effects in result sets, with the goal to avoid unintended biases in decision processes. If such item constellations are detected,

[1] Simplified version of the dominance metric presented by Felfernig et al. (2008a).

Table 10.7. *Calculation of dominance values for $x \in CSet$ (items from Table 10.3).*

	x	y_1	y_2	*sum*	$d(x, CSet)$
	A	**B**	**D**		
price per month		−0.67	0.33	−0.33	
download limit		1.0	0.25	1.25	
					0.92
	B	**A**	**D**		
price per month		0.67	1.0	1.67	
download limit		−1.0	−0.75	−1.75	
					−0.08
	D	**A**	**B**		
		−0.33	−1.0	−1.33	
		−0.25	0.75	0.5	
					−0.83

additional items (neutralizing items) must be added or identified decoy items must be deleted – this can be interpreted as a type of result set configuration problem (Teppan and Felfernig 2009b). Exploiting models of decision biases for neutralizing purposes is extremely important for more customer-centered recommendation environments that are aware of decision biases and try to avoid those when otherwise suboptimal decisions would lead to unsatisfied customers and sales churn. Currently, research focuses on understanding different effects of decision biases but not on how to effectively avoid them. Initial results of empirical studies regarding avoidance aspects are reported by Teppan and Felfernig (2009a).

10.3 Primacy/recency effects

Primacy/recency effects as a cognitive phenomenon describe situations in which information units at the beginning and at the end of a list of items are more likely remembered than information units in the middle of the list[2].

[2] These effects are also called *serial position effects* (Gershberg and Shimamura 1994, Maylor 2002).

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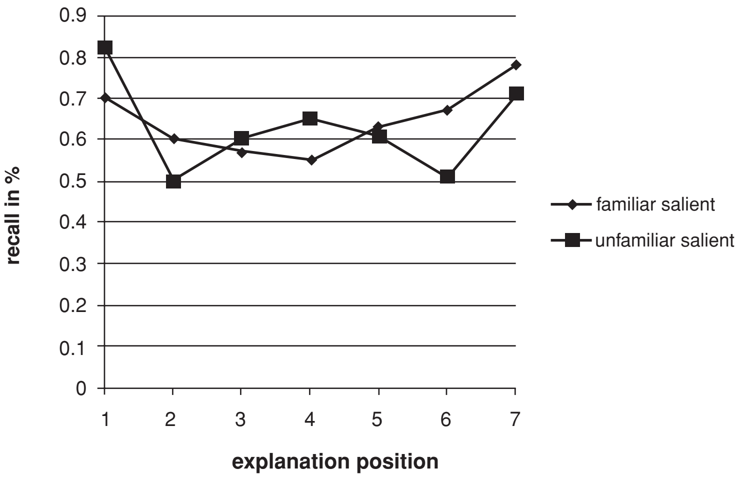

Figure 10.1. Primacy/recency effects in item explanations.

Thus, primacy/recency shows two recall patterns: on one hand, elements at the beginning of a list (primacy) and, on the other hand, elements at the end of a list (recency) are recalled more often than those positioned in the middle of a list. Primacy/recency effects in recommendation dialogs must be taken into account because different question sequences can potentially change the selection behavior of consumers (Häubl and Murray 2003). The existence of different types of serial position effects in knowledge-based recommender applications is also analyzed by Felfernig et al. (2007a). This study indicates that product explanations positioned at the beginning and at the end of a list of explanations are remembered more often than those explanations positioned in the middle of a list (see Figure 10.1). The two curves in Figure 10.1 represent two different explanation lists. The first one is denoted as *familiar salient*, in which explanations related to well-known item properties are positioned at the beginning and the end of the list. The second one is denoted as *unfamiliar salient*, in which explanations related to less familiar properties are positioned at the beginning and the end of the list.

Primacy/recency effects as a decision phenomenon describe situations in which items presented at the beginning and at the end of a list are evaluated significantly more often compared with items in the middle of a list. Significant shifts in selection behavior that are triggered by different element orderings on a recommender result page are reported by Felfernig et al. (2007a). The same

Table 10.8. *Utility function for primacy/recency effects.*

item position(i)	1	2	3	4	5
posutility(i)	5	3	1	3	5

phenomenon exists as well in the context of web search scenarios (Murphy et al. 2006): web links at the beginning and the end of a list are activated significantly more often than those in the middle of the list. Typically, users are not interested in evaluating large lists of items to identify those that best fit their wishes and needs. Consequently, a recommender application must calculate rankings that reduce the cognitive overheads of a user as much as possible.

An approach to take into account primacy/recency effects in the presentation of items on product result pages was introduced by Felfernig et al. (2008c). Assuming that we have n items in a result set, we have $n!$ permutations of orders in which items can be presented. Typically, in knowledge-based recommender applications, the utility of items is determined on the basis of multiattribute utility theory (MAUT; Winterfeldt and Edwards 1986), which calculates a ranking r for each item contained in the result set. MAUT-based ranking does not take primacy/recency effects because items are presented in the order of decreasing utility values. A way to take serial position effects in MAUT-based rankings into account is presented in Formula 10.2 (Felfernig et al. 2008c).

$$orderutility([p_1, p_2, \ldots, p_n]) = \sum_{i=1}^{n} utility(p_i) * posutility(i) \tag{10.2}$$

In Formula 10.2, $orderutility([p_1, p_2, \ldots, p_n])$ specifies the overall utility of the sequence $[p_1, p_2, \ldots, p_n]$, utility(p_i) specifies the MAUT-based utility of a specific item contained in the result set, and $posutility(i)$ specifies the utility of a specific position i. To take primacy/recency effects into account, the function $posutility(i)$ could be specified as shown in Table 10.8: prominent positions at the beginning and the end of the product list have a higher value determined by *posutility*. Note that in this simple example we assume that every recommendation result consists of exactly five items.

This principle of ranking items in the evaluation of result sets is also applied in the context of automated explanation generation in the domain of buildings (Carenini and Moore 2006). Such explanations include a set of arguments that help a user understand why a certain item has been recommended.

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10.4 Further effects

Framing denotes the effect that the way a decision alternative is presented influences the decision behavior of the user (see, e.g., Tversky and Kahneman 1986).

The way pricing information is presented to a user significantly influences the way in which other attributes of a certain decision alternative are evaluated (Levin et al. 1998). This specific phenomenon is denoted as *price framing*: if price information is provided for subcomponents of a product (e.g., the memory unit), then users put more focus on the evaluation of those subcomponents because price information is provided on a more detailed level. Conversely, if an all-inclusive price is presented (e.g., the price for the camera including the memory unit), then users focus their evaluation on important item properties (e.g., the resolution or zoom).

Attribute framing denotes the phenomenon that different but equivalent descriptions of a decision task lead to different final decisions. For example, a financial service described with 0.98 probability of no loss is evaluated better than an equivalent service described with 0.02 probability of loss (valence consistency shift [Levin et al. 1998]). As another example, consumers prefer to buy meat that is 80 percent lean compared with meat that is 20 percent fat. Consumers who are highly familiar with a specific type of product are less amenable to framing effects, as they have clear preferences that should be fulfilled by the recommended product (Xiao and Benbasat 2007).

Priming denotes the idea of making some properties of a decision alternative more accessible in memory, with the consequence that this setting will directly influence the evaluations of a consumer (McNamara 1994; Yi 1990). *Background priming* (Mandel and Johnson 1999) exploits the fact that different page backgrounds can directly influence the decision-making process. An example of background priming is provided by Mandel and Johnson (1999), in which one version of an online furniture selling environment had a background with coins and the second version had a cloudy background (cirrocumulus), which triggered feelings such as *comfort* or *silence*. Users who interacted with the first version chose significantly less expensive products compared with those who interacted with the cloudy-background version.

Priming effects related to the inclusion or exclusion of certain product attributes are discussed by Häubl and Murray (2003). Participants in a user study had the task of selecting a backpacking tent in an online store. The participants were supported by a recommendation agent that collected preference information regarding different properties of tents. One group of participants was asked to specify importance values regarding the properties *durability* and *flynet*; the other group had to specify importance values regarding the properties *warranty* and *weight*. The recommender application then ordered the set of attributes to conform to the preferences specified by the participant (all available tents were visible for both groups). Finally, the participants had to select their favorite item. The result of this study was that participants chose items that outperformed other items in exactly those properties asked by the recommender application. Consequently, human decision-making processes can be influenced systematically by selective presentations of properties in the dialog.

An aspect related to priming is the reduction of questions in a recommendation dialog with the goal to reduce factors such as the dissatisfaction with a choice made or even the aversion to make a decision (Fasolo et al. 2007). Furthermore, the systematic reduction of choice alternatives in choice sets can lead to increased purchase rates (Hutchinson 2005).

Defaults play an important role in decision-making processes because people often tend to favor the status quo compared with other potentially equally attractive decision alternatives (Ritov and Baron 1992, Samuelson and Zeckhauser 1988). This tendency to maintain decisions and being reluctant to change the current state is also called *status quo bias* (Samuelson and Zeckhauser 1988). Potential changes to the current state are always related to some kind of losses or expected gains – and people are typically loss-averse (Tversky and Kahneman 1984, Ritov and Baron 1992). If default options are used in the presentation of decision alternatives, users are reluctant to change this setting (the current state). This phenomenon is able to trigger biases in decision processes (Herrmann et al. 2007, Ritov and Baron 1992). Consumers tend to associate a certain risk with changing a default, as defaults concerns are interpreted to be a central part of a company's product design. Thus a typical application of defaults concerns properties with an associated risk if not selected (e.g., safety equipment in cars, investment protection, or warranties with electronic equipment).

Besides triggering biasing effects, defaults can also reduce the overall interaction effort with the recommender application and actively support consumers in the product selection process – especially in situations in which consumers do not have a well-established knowledge about the underlying product assortment. For example, when buying a digital camera, a default value regarding the needed storage medium could be helpful. Furthermore, defaults can increase the subjectively felt granularity of recommender knowledge bases, as consumers will tend to think that companies really tried to do their best to explain and present the product assortment. Finally, defaults could be used to manipulate the customer in the sense that options are recommended that are of very low or no value for the customer but of value to the seller.

10.5 Personality and social psychology

Besides the cognitive and decision psychological phenomena discussed in the previous sections, different personality properties pose specific requirements on the design of recommender user interfaces. A detailed evaluation of personality properties is possible but typically goes along with considerably efforts related to the answering of large questionnaires. A widespread questionnaire used for identification of personality properties is the NEO Five-Factor Inventory (NEO-FFI; McCrae and Costa 1991), which requires the answering of sixty different questions. There are few application scenarios in which users will accept such an overhead. In this section, we focus on scenarios in which such a detailed personality analysis is not needed.

Locus of control (LOC) can be defined as the amount a human being is able to control occurring events (Duttweiler 1984; Kaplan et al. 2001). The relevance of LOC for the design of recommender user interfaces is explained simply by the fact that users should be able to decide on their own with which type of interface they prefer to interact. Predefined and static dialogs better support users without a special interest in controlling the recommendation process (*external LOC*), whereas more flexible dialogs better support users with a strong interest in controlling the recommendation process (*internal LOC*). More flexible recommender user interfaces not only let the user select the parameters they want to specify but also actively propose interesting parameters and feature settings (Mahmood and Ricci 2007, Tiihonen and Felfernig 2008). Recent research starts to differentiate among influence factors on LOC. For example, the application domain has a major impact on the orientation of LOC – a user could be an expert in the domain of digital cameras but be a nonexpert in the domain of financial services. Such factors are systematically analyzed in the *attribution theory* developed by Weiner (2000).

Need for closure (NFC) denotes the individual's need to arrive at a decision as soon as possible and to get feedback on how much effort is still needed to successfully complete a decision task (Kruglanski et al. 1993). It also refers to a tendency of people to prefer predictability and to narrow down the efforts of an information search as much as possible. Recommender applications can take into account the NFC, for example, by the inclusion of progress bars that

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inform about the current status of the overall process and the still open number of questions. An example for such a *progress indication* is shown in Figure 4.9, in which the user gets informed about the current status of the recommendation process in terms of the currently active phase. Another concept that helps to take into account the NFC is an immediate display of temporary recommendation results such that the user has the flexibility to select an item for detailed inspection whenever he or she wants. Finally, automated repair actions (see the chapter on knowledge-based recommendation) also help to take into account the NFC (immediate help to get out from the dead end).

Maximizer and satisficer (MaxSat) are two further basic behavioral patterns (Kruglanski et al. 1993, Schwartz et al. 2002). *Maximizers* interacting with a recommender application typically need a longer time span for completing a session because they prefer to know many technical details about the product and, in general, tend to identify an optimal solution that requires an exhaustive search over the available decision alternatives. In contrast, *satisficers* are searching for "good enough" solutions until one solution is found that is within an acceptability threshold. A simple example for the behavioral pattern of maximizers and satisficers is the selection of TV channels (Iyengar et al. 2006). Satisficers focus on the identification of a channel that offers the first acceptable program, whereas maximizers spend most of the time on selection activities such that, compared to satisficers, significantly less viewing time is available for them.

Maximizer and satisficer personality properties can be derived directly by analyzing the interaction behavior of the current user. For example, if a user continually focuses on a detailed analysis of technical product properties, the user can be categorized as a maximizer. Personality properties can then be used, on one hand, when presenting recommendations on a result page by giving more application-oriented or more technical explanations, and on the other hand, throughout the dialog phase by giving more technical or nontechnical explanations, hints, information about already given answers, or information about open questions. Interestingly, Botti and Iyengar (2004) and Iyengar et al. (2006) report results of studies in which maximizers have a tendency to more negative subjective evaluations of decision outcomes ("post-decision regret"), which makes the outcome of a decision process harder to enjoy. This could be explained by the fact that maximizers tend to underestimate the affective costs of evaluating as many options as possible, which contradicts with the assumption of psychologists and economists that the provision of additional alternatives always is beneficial for customers (Botti and Iyengar 2004, Iyengar et al. 2006).

Conformity is a process in which a person's behaviors, attitudes, and beliefs are influenced by other people (Aronson et al. 2007). In the line of this definition, recommenders have the potential to affect users' opinions of items (Cosley et al. 2003).

Empirical studies about conformity effects in a user's rating behavior in CF applications are presented by Cosley et al. (2003). The authors investigated whether the display of item predictions affects a user's rating behavior. The outcome of this experiment was that users confronted with a prediction significantly changed (adapted) their rating behavior. The changed rating behavior can be explained by the fact that the display of ratings simply influences people's beliefs. This occurs in situations in which item evaluations are positively or negatively manipulated: in the case of higher ratings (compared with the original ratings), users tend to provide higher ratings as well. The effect also exists for lower ratings compared with the original ratings.

In summary, the recommender user interface can have a strong impact on a user's rating behavior. Currently, with a few exceptions (Beenen et al. 2004), collaborative recommender systems research focuses on well-tuned algorithms, but the question of user-centered interfaces that create the best experiences is still an open research issue (Cosley et al. 2003). Another example for related research is that by Beenen et al. (2004), who investigated the impact of positive user feedback on the preparedness for providing item ratings. The result of the study was significant: users who got positive feedback (ratings are really needed in order to achieve the overall goal of high-quality recommendations) on their ratings rated more frequently.

Trust is an important factor that influences a consumer's decision whether to buy a product. In online sales environments, a direct face-to-face interaction between customer and sales agent is not possible. In this context, trust is very hard to establish but easy to lose, which makes it one of the key issues to deal with in online selling environments. Notions of trust concentrate mainly on improvements in the dimensions of security of transactions, privacy preserving applications, reputation of the online selling platform, and competence of the recommendation agents (Chen and Pu 2005, Grabner-Kräuter and Kaluscha 2003). A customer's willingness to buy or return to a web site are important trust-induced benefits (Chen and Pu 2005, Jarvenpaa et al. 2000).

Trust-building processes in the context of recommender systems depend strongly on the design of the recommender user interface and the underlying recommendation algorithms (Chen and Pu 2005, Felfernig et al. 2006). Major elements of a recommender user interface that support trust building are explanations, product comparisons, and automated repair functionalities (Felfernig et al. 2006a). Explanation interfaces (Pu and Chen 2007) are an important means to support recommender system transparency in terms of arguments as to why a certain item has been recommended or why certain critiques[3] have been proposed. Significant increases in terms of trust in the recommender application have been shown in various user studies – see, for example, Felfernig et al. (2006a) and Pu and Chen (2007). Product comparisons also help a user establish a higher level of trust in the recommender application. This can be explained simply by the fact that comparison functionalities help to decrease the mental workload of the user because differences and commonalities among items are clearly summarized. Different types of product comparison functionalities are available on many e-commerce sites – for example, www.amazon.com or www.shopping.com (Häubl and Trifts 2000). Finally, repair actions are exploited by users with a low level of product domain knowledge; in this context, repair actions help to increase the domain knowledge of the user because they provide explanations why no recommendation could be found for certain combinations of requirements (Felfernig et al. 2006a). Repair actions are typically supported by constraint-based recommender applications – an example for a commercially available application is discussed by Felfernig et al. (2007b). The second major factor that influences the perceived level of trust is the overall quality of recommendations – the higher the conformity with the user's real preferences, the higher is the trust in the underlying recommender algorithm (Herlocker et al. 2004).

Emotions. Although the importance of extending software applications with knowledge about human emotions is agreed on (Picard 1997), most of the existing recommender applications still do not take this aspect into account (Gonzalez et al. 2002). User profiles typically do not include information about human emotions, and as a consequence, recommender applications are, in many cases, unable to adapt to the constantly changing and evolving preferential states. An *emotion* can be defined as "a state usually caused by an event of importance to the subject. It typically includes (a) a conscious mental state with a recognizable quality of feeling and directed towards some object, (b) a bodily perturbation of some kind, (c) recognizable expressions of the face, tone of voice, and gesture [and] (d) a readiness for certain kinds of action" (Oatley and Jenkins 1996). There are different, but not well agreed on, approaches to categorizing emotional states (Parrot 2001). One categorization that is also applied by the commercially available movie recommendation environment

[3] Critiquing has been described earlier.

Table 10.9. *Emotion categories used in* MovieProfiler *(originally, this set of emotions was developed by Plutchik and Hope [1997]).*

Emotion	Description
Fear	A feeling of *danger* and/or *risk* independent of the fact of being real or not
Anger	Status of *displeasure* regarding an action and/or an idea of a person or an organization
Sorrow	Status of *unhappiness* and/or *pain* because of an unwanted condition and the corresponding emotion
Joy	Status of being *happy*
Disgust	Associated with things and actions that appear "*unclean*"
Acceptance	Related to *believability*, the degree to which something is accepted as true
Anticipation	Expectation that *something* "*good*" *will happen*
Surprise	Emotion triggered by an *unexpected event*

MovieProfiler[4] has been developed by Plutchick (see, e.g., Plutchik and Hope 1997) – the corresponding emotion types are explained in Table 10.9. The search engine of MovieProfiler supports item search on the basis of an emotional profile specified by the user (see Figure 10.2). The search engine follows a case-based approach in which the most similar items are retrieved by the application. The innovative aspect of MovieProfiler is the search criteria that are represented as emotional preferences that define which expectations a user has about a recommended movie. A user indicates on a five-point psychometric scale which specific emotions should be activated by a film. In a similar way, users are able to evaluate movies regarding the emotions *fear*, *anger*, *sorrow*, *joy*, *disgust*, *acceptance*, *anticipation*, and *surprise* (see Figure 10.3).

Persuasion. Behavioral decision theory shows that human decision processes are typically based on adaptive decision behavior (Payne et al. 1993). This type of behavior can be explained by the *effort-accuracy tradeoff*, which states that people typically have limited cognitive resources and prefer to identify optimal choices with as little effort as possible. The aspect of the availability of limited cognitive resources is also relevant in the theory of decision making under bounded rationality (Simon 1955); bounded rationality can act as a door opener for different nonconscious influences on the decision behavior of a consumer. This way of explaining human decision processes has a

[4] www.movieprofiler.com.

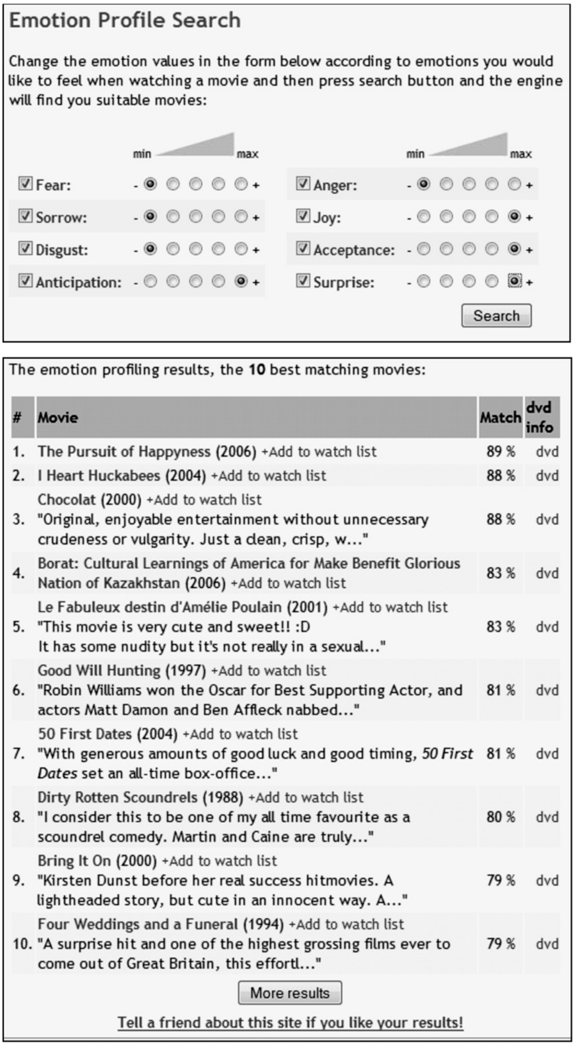

Figure 10.2. MovieProfiler recommender – emotion-based search: the user specifies requirements in terms of emotions (*fear*, *anger*, *sorrow*, *joy*, *disgust*, *acceptance*, *anticipation*, and *surprise*) that should be activated when watching the movie.

major impact on the perceived role of recommender applications, which now moves from the traditional interpretation as tools for supporting preference *elicitation* toward an interpretation of tools for preference *construction*. As discussed in the previous sections, the design of a recommender application can have a significant impact on the outcome of a decision process (Gretzel and

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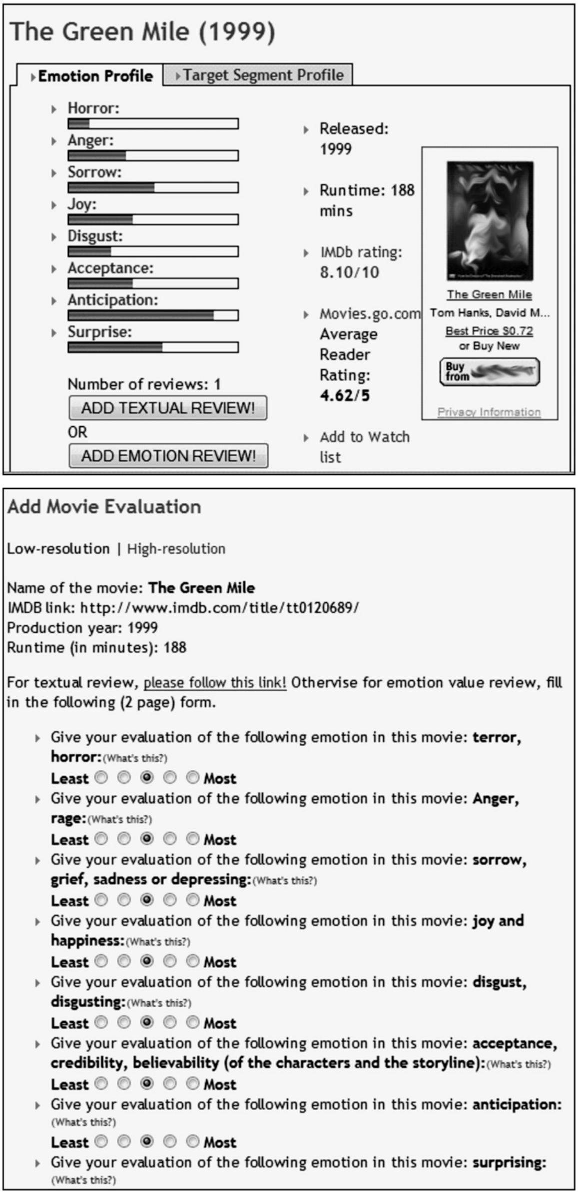

Figure 10.3. MovieProfiler recommender – evaluation of movies: movies can be evaluated regarding the emotions *fear*, *anger*, *sorrow*, *joy*, *disgust*, *acceptance*, *anticipation*, and *surprise*.

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Fesenmaier 2006). Consequently, recommender technologies can be interpreted as persuasive technologies in the sense of Fogg: "Persuasive technology is broadly defined as technology that is designed to change attitudes or behaviors of the users through persuasion and social influence, but not through coercion" (Felfernig et al. 2008c, Fogg 2003). This interpretation is admissible primarily if recommendation technologies are applied with the goal of supporting (not manipulating) the customer in finding the product that fits his or her wishes and needs. Obviously, persuasive applications raise ethical considerations, as all of the effects mentioned here could be applied to stimulate the customer to purchase items that are unnecessary or not suitable.

10.6 Bibliographical notes

Consumer buying behavior and decision making have been studied extensively in different research areas, such as cognitive psychology (Gershberg and Shimamura 1994, Maylor 2002), decision psychology (Huber et al. 1982, Yoon and Simonson 2008), personality psychology (Duttweiler 1984, Weiner 2000), social psychology (Beenen et al. 2004, Cosley et al. 2003), and marketing and e-commerce (Simonson and Tversky 1992, Xiao and Benbasat 2007). Predominantly, the reported results stem from experiments related to isolated decision situations. In many cases, those results are not directly applicable to recommendation scenarios without further empirical investigations that take into account integrated recommendation processes. The exception to the rule is Cosley et al. (2003), who analyze the impact of social-psychological effects on user behavior in the interaction with collaborative filtering recommenders. Furthermore, Felfernig et al. (2007, 2008a, 2008c), and Häubl and Murray (2003, 2006) focus on the integration of research results from marketing and decision psychology into the design of knowledge-based recommender applications. The investigation of culture-specific influences on the acceptance of user interfaces has been the focus of a number of studies – see, for example, Chau et al. (2002), Chen and Pu (2008), and Choi et al. (2005). From these studies it becomes clear that different countries have different cultural backgrounds that strongly influence individual preferences and criteria regarding user-friendly interfaces. Significant differences exist between Western cultures that are based on individualism and Eastern cultures that focus more on collectivistic elements. A more detailed analysis of culture-specific influences on the interaction with recommender applications has first been presented in Chen and Pu (2008).