Chapter 2

Recommender Systems – Definition, Classification, and Marketing Perspectives

This chapter deals with recommender systems from a marketing perspective. First, working definitions of the book are established. Section 2.2 introduces a general classification of recommender systems. In this taxonomy recommender systems are classified along user adaption (i.e. personalization aspects), mode of information delivery, method of data acquirement, and recommendation methods. Furthermore, requirements of an “ideal” recommender systems are presented.

Section 2.3 elaborates on different application models of recommender systems. These application models are tied to specific business goals. These goals are: (1) turning visitors into buyers, (2) building credibility through community, (3) inviting customers back, (4) cross-selling, and (5) building long term relationships. Application models and their corresponding business goals are exemplified by illustrating use cases in different companies or research institutions on the Internet.

Section 2.4 deals with the consumer decision process. As recommender systems are designed to assist the consumer in this process, understanding the consumer decision process is an important issue. A phase model of the consumer decision
process as proposed by Blackwell et al. is set out [BME01]. In this model all fundamental constructs of consumer behavior in regard to the decision process are integrated and interrelated. It includes the following seven phases: (1) need recognition, (2) search for information, (3) pre-purchase evaluation of alternatives, (4) purchase, (5) consumption, (6) post-consumption evaluation, and (7) divestment. The section describes, how consumers may be supported in these phases by recommender systems.

The last section of this chapter addresses virtual communities and their relevance for recommendation purposes. Characteristics and benefits of virtual communities of transaction (i.e. virtual communities, whose focus is on the transaction of products and services) are presented. Further, the importance of network effects in virtual communities is highlighted. The section ends with a description of community building aspects.

2.1 Working Definitions

Recommender systems are information systems, that assist the user in making choices without sufficient personal experience of the alternatives. This is achieved by providing information about the relative merits of alternative courses of action [RV97, SV99]. In contrast to traditional decision support systems, which are predominately used by specialists (e.g. managerial decision makers), recommender systems are designed to support consumers in the decision making process [HN05, TA01, SV99]. In the context of e-commerce applications recommender systems are used to suggest products and services to users [Bur02, SKR01].

Recommender systems are also referred to as recommendation systems. In early publications (e.g. [GNOT92, RV97]) the term recommender system was closely tied to a specific method of generating recommendations – namely collaborative filtering. This perspective limits recommender systems to a group of systems which uses a distinct method of generating recommendations (methodical view). Because of this narrower perspective the term recommendation system was proposed as a broader term, which denotes a system whose objective is to give recommendations regardless of the underlying recommendation
method (functional view) [SV99]. However, nowadays the term recommender system is more frequently used in literature for both perspectives.

In this book the following working definitions are used:

- A recommender system is an information system, that assists consumers in making product choices by providing recommendations of the range of products and services offered by an e-commerce application.
- The term item refers to the artifact (e.g. a certain product), that is suggested to a consumer by a recommender system.
- The active user is the consumer, for whom recommendations are generated.
- In the context of this book, personalization denotes the adaptation of recommendations to the active user based on knowledge (e.g. the user's preferences and behavior) about that certain user.

The main objectives of recommender systems are to reduce information overload and improve decision quality [Run00]. Information overload occurs because e-commerce stores may offer a wider range of products and services to the customer compared to traditional brick and mortar stores. In e-commerce stores the offered mix of products and services is not limited to physical space restrictions of the sales room. Thus, recommender systems are used to offer a subset of the product and service mix to the consumer to reduce information overload. Further objectives may be to provide personalized product information, rank items (i.e. products) according to the individual user profile, forecast user preferences for a distinct item, provide community critiques, and summarize community opinion [Run00, SKR01].

2.2 Classification

Figure 2.1 shows a classification of recommender systems that considers four dimensions and gives an overview of the design alternatives of recommender systems:
1. User adaptation: Recommender systems can be categorized into personalized and non-personalized recommender systems [Run00]. Non-personalized recommender systems give identical recommendations to different users. In contrast, personalized recommender systems adapt their suggestions to individual users. Depending on the persistency of the user profile, ephemeral and persistent personalization can be distinguished [MT02]. Ephemeral personalization uses current user interaction data (e.g. the items in the shopping cart) to adapt suggestions to the user. However, if the user terminates the interaction session, the input data will be lost. Persistent personalization goes beyond ephemeral personalization. It requires that the user is identified (for instance by a username and password combination) over different sessions. Persistent personalization stores the user interaction data permanently. It allows improving the accuracy of the user profile over time and thus enables to tailor recommendations more specifically to the user's needs.

2. Information delivery: Recommendations can be sent to the customer in different ways. Recommender systems based on push technologies initiate the communication process. Push communication can be used to forward recommendations by e-mail even when the customer is currently not in-
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teracting with the e-commerce application. *Pull technologies* require the customer to explicitly request recommendations, i.e. the communication process is initiated and controlled by the user [MGL97]. *Passive recommendation delivery* refers to presenting the recommendation in the natural context of the e-commerce application (e.g. displaying recommendations during viewing or ordering a product). The advantage of this approach is to give recommendations when the user is already receptive to the idea of buying or consuming articles [SKR01].

3. Data acquirement: Recommender systems require input data from users to suggest items. This may be achieved by explicit user interrogation or implicit user monitoring. *Explicit data acquirement* demands the user to intentionally inform the recommender systems about his preferences. In e-commerce applications this is usually achieved by filling out web-based forms. *Implicit data acquirement* is achieved by monitoring user behavior. Thus active user involvement is not required in the knowledge acquisition task (e.g. monitoring the time a user spends reading a description of a product as an indicator of interest) [HSS01].

4. Recommendation method: *Manual selection* refers to manually created and updated lists of recommendations. This is usually conducted by experts (e.g. editors, critics), who rank items according to their individual tastes, interests, and objectives. This method does not require machine-based computation at all. Those manually generated recommendation lists are simply posted on a web site. *Statistical summarization* is generally used to sum up community opinions about an item. *Information filtering methods* are more sophisticated recommendation techniques. In contrast to manual selection and statistical summarization, information filtering techniques deliver personalized recommendations. Information filtering applies user profiles to generate recommendations adapted to the user's interests. The most popular information filtering approaches are collaborative and attribute-based filtering.

A detailed description of these functional aspects of recommender systems based on this classification scheme can be found in Chapter 3.
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Recommender systems may combine different methods of data acquisition, information delivery, and recommendation and vary the degree of personalization to best fit the user’s needs [Bur02, BHC98, BS97]. It may be useful to forego personalization in early stages of customer interaction. At this stage, data in the user profile is still sparse, trust in the e–vendor may be low and concerns regarding privacy may be high. Thus non–personalized recommendations based on statistical summarization or manual selection may be a good starting point to foster the relationship with the customer. After the successful establishment of a relationship and having overcome the initial barriers the e–vendor may add personalized recommendations to the customer interaction. For example amazon.com applies 18 different types of recommender systems with varying degrees of personalization, different methods of information delivery, diverse recommendation methods and varying input data on their web–site [GGSHST02].

Hence, an ideal recommender system should [AEK00]:

- apply different types of information (e.g. active user preferences, active user characteristics, community preferences, experts judgements),
- use appropriate methods of data acquirement (implicit, explicit),
- employ adequate recommendation methods (e.g. personalized, non–personalized methods, collaborative filtering, attribute–based filtering),
- explain reasons behind recommendations,
- provide estimates of accuracy of recommendations,
- incorporate dynamic learning (more information about the active user should lead to better recommendations for the active user and possibly for other users) and
- show adequate response times in respect of the delivery of recommendations and the adaption to the users’ preferences.
2.3 Application Models of Recommender Systems

As mentioned in Section 2.1 from a user's (i.e. the customer's) perspective recommender systems reduce information overload, provide personalized product information, rank items, forecast user preferences, provide community critiques, and summarize community opinion. From the e–vendor point of view recommender systems ideally assist him or her in turning new and infrequent visitors of the web-site into buyers, building credibility through community inputs, inviting customers back, improving cross sales, and building long term relationships [SKR01]. Figure 2.2 shows five application models of recommender systems with their corresponding business goals. The degree of personalization – i.e. the extent of treating each customer individually – increases from the bottom to the top.

### 2.3.1 Broad Recommendation Lists

One of the most compelling challenges for e–commerce vendors is to turn visitors into buyers. Especially new and infrequent visitors need support in the navigational process to direct them to engaging products. E–commerce sites
use broad recommendation lists to give an overview of the range of products and services. The recommendations presented to the customer are not personalized and manual selection or statistical summarization are employed as preferred recommendation methods. These broad recommendation lists typically include overall best sellers, best sellers in a category, experts recommendations and other collections generated through manual selection or statistical summarization [SKRO1].

Figure 2.3 shows an application of broad recommendation lists at Barnsandnoble.com. These broad recommendation lists are based on sales of Barnsandnoble.com and are updated hourly. Besides the overall best sellers in the category “books” this e–vendor offers best sellers lists in other product categories (e.g. DVDs, videogames etc.) as well as best seller lists in different subcategories of books (e.g. adult fiction, business).

One major advantage of broad recommendation lists is the low degree of personalization. Thus the required amount of personal information about the user is low (e.g. ephemeral context information about the category of interest to the user). This makes broad recommendations appropriate in early stages of customer interaction, when the customer is reluctant to give personal information to the e–vendor. Products suggested in broad recommendation lists are inherently appealing to the majority of the customers. Hence, they are not suitable for users interested in niche products. Without personalized recommendations it is indeed very difficult to meet the taste of these users.

### 2.3.2 Customer Comments and Ratings

Another business goal e–commerce vendors try to achieve with recommender systems is to build credibility through community. The e–commerce application should support the community of users as a platform for customer comments and ratings. This may help to overcome the problem of a possible initial distrust of the customer in the e–vendor. Usually customer comments and ratings are displayed in addition to the e–vendor’s product descriptions. They function as a trust building measure, because the customers usually have more confidence in the opinion of other customers [SKR01].
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Figure 2.3: Barnsandnoble.com overall best seller list in the category “books”

Figure 2.4 illustrates customer comments and ratings at the Amazon.com. The user may rank the product based on an ordinal scale from one to five. In addition to this purely quantitative rating a qualitative review in form of a textual description (limited to 1000 words) is also possible. These textual reviews are of major importance especially when personal taste is a significant criterion for the purchase of the product (e.g. books, music). Amazon.com uses mechanisms to ensure quality of the customer reviews by enabling other users to submit meta-recommendations for reviews. The reviews voted most useful by the Amazon.com community are displayed first (“Spotlight reviews”). Further Amazon.com has set up several incentives (e.g. vouchers) to enhance community activities.
An advantage of customer comments and ratings is that they require little effort by the e–vendor because all evaluation is done by the customers. However, the e–vendor must focus on usability of the e–commerce application to provide a comfortable platform for community communication and provision of advice or feedback on products. As a further benefit, community related initiatives may help to distinguish the e–vendor from competitors.

2.3.3 Notification Services

Notification services are an application of push communication in recommender systems to invite existing customers back to the store and increase sales. Noti-
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Notifications are typically sent via e-mail when new products are in stock or special offers are available. A simple and often used form of notification services enables the customer to specify attributes (e.g. category of music or book, price range) of products he or she is interested in. When the desired products are available, the user gets a message from the e-vendor. These services are a good starting point for individualized customer interaction.

Figure 2.5 shows an example of a simple notification service based on user pre-selections. Educanext.org is a platform for exchanging higher education learning resources. The user may subscribe to different academic disciplines he or she is interested in. When new learning resources in the specified fields are uploaded to the platform, the user receives an e-mail that lists titles and authors of these new resources.

However, more complex personalization techniques go beyond these simple pre-selections of attributes by the user. They monitor user behavior, build dynamic user profiles and adapt recommendations towards individual users based on the profiles.

2.3.4 Product Associated Recommendations

A further business goal for recommender systems is to increase cross-sales by means of product-associated recommendations. In brick-and-mortar stores complementary products are arranged nearby to encourage cross-sales. Since e-vendors do not have this spatial arrangement opportunity, recommender systems may suggest related products. Moreover recommender systems may go a step further and use the user profile to provide personalized cross-sales lists. A variety of input data may be used to generate such cross-sales lists. This includes anonymous purchase histories, customer purchase histories, ratings, product attributes, and expert opinions [SKR01]. Another option is to use explicit community knowledge to create or improve such lists.

As shown in Figure 2.6 Musicstore.de suggests complementary products ("suitable accessories") based on specific product attributes. As a further example, Amazon.com employs past buying behavior of other users to create such cross-sales lists ("Customers who bought this title also bought"). In addition
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customers from Amazon.com may be explicitly recommended complementary items ("Our customers’ advice").

2.3.5 Persistent Personalization

One of the most challenging goals of recommender systems is to build long-term relationships. Long-term relationships should increase sales volume per customer and should help the e-vendor to build competitive barriers. This may be achieved by persistent personalization. Personalized recommender systems are based on the customer’s history of preferences, purchases, or navigation and try to meet the needs of each individual customer. Personalized recom-
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mender systems dynamically learn user interests and store them in the user profile of the customer each time he or she interacts with the e-commerce application [SKR01].

Usually personalized recommender systems use information filtering techniques (e.g. user-based collaborative filtering) to address each customer individually. Persistent personalization raises competitive barriers, because by and by the e-vendor can meet the customers' needs more specifically and improve loyalty. The time consuming character of the learning relationship between e-vendor and customer hinders the customer to switch to another e-vendor easily (i.e. switching costs).
Figure 2.7 illustrates personalized recommendations at Movielens.emu.edu by applying collaborative filtering in conjunction with explicit user input. Movielens is a non-commercial research site run by GroupLens Research at the University of Minnesota. On this site the user explicitly rates movies he has already seen. This information is stored permanently in the user profile.
2.4 The Consumer Decision Process

As mentioned in Section 2.1 recommender systems assist the consumer in the decision making process. Hence, understanding this process may provide helpful insight when a vendor plans to apply a recommender system. In this section a holistic model of the consumer decision process as proposed by Blackwell et al. is presented [BME01]. In contrast to partial models of consumer behavior, holistic models try to integrate and interrelate all fundamental constructs of consumer behavior in regard to the decision process [Mef00]. Figure 2.8 shows the *phase model* of this process [BME01], that includes seven phases: (1) need recognition, (2) search for information, (3) pre-purchase evaluation of alternatives, (4) purchase, (5) consumption, (6) post-consumption evaluation, and (7) divestment. This model represents a roadmap of consumers’ minds, which is relevant with respect to recommendation applications of e-vendors. Consumers may be supported in the individual phases by recommender systems as described in the following sections.

2.4.1 Need Recognition

*Need recognition* occurs, when an individual senses a difference between what he or she perceives to be ideal in contrast to the actual state [BME01]. As shown in Figure 2.9, need recognition appears, when a certain degree of discrepancy between the actual state (i.e. the consumer’s current situation) and the desired state (i.e. the situation a consumer wants to be in) appears. When a given level of threshold is reached, the consumer becomes aware that he or she has a need, that probably can be satisfied through a product or service.

Need recognition may either happen for reasons outside the control of a company or may be influenced by businesses. Advertising is a possible instrument for companies to generate needs [OM98]. Especially personalized recommendations provided by recommender systems can be understood as a form of “advertising tailored towards the individual”. Hence, recommender systems may be used to create or stimulate these needs more efficiently. In this stage of the consumer decision process push-communication may be a reasonable
2.4.2 Information Search

*Information search* is the next step in the consumer decision process model. Once a need is recognized, consumers start to search for information to satisfy the unmet needs. This search may occur *internal or external*. Internal search refers to retrieving decision-relevant knowledge from memory. In contrast ex-
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External search occurs when the consumer is collecting information from the marketplace, peers or other relevant information sources. Figure 2.10 shows the connection between internal and external search. External search usually occurs after the internal search process [Pun87]. If the consumer thinks that his knowledge is inadequate for the purchase decision he or she probably will undertake external search. This may happen passively (i.e. the consumer becomes more receptive to information sources) or actively, when the consumer exhibits search behavior like screening consumer publications, advertising material, web-sites or venturing retail outlets. External search can be categorized in pre-purchase search and ongoing search. Pre-purchase search is motivated by an upcoming purchase decision, whereas ongoing search is happening on a regular basis regardless of sporadic purchase needs [Pun87, BME01]. Recommender systems may be used to assist the consumer in both categories of external search. For instance, if a book enthusiast gets recommendations of new publications in his or her fields of interests sent by e-mail on a regularly basis, he or she is supported in the process of ongoing search.

When the consumer applies external search the following steps are involved to process information [BME01]:

![Diagram of the need recognition process](image)
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• Exposure: In this phase the information reaches the consumer, whereby the senses of the consumers are activated and preliminary processing begins.

• Attention: This refers to the allocation of information-processing capacity of the consumer to incoming information. The higher consumers judge the degree of relevancy of the message, the more likely they will pay attention.

• Comprehension: The consumers analyze the message against categories of meaning already stored in memory.

• Acceptance: Once comprehension is achieved, the message could be accepted or dismissed as unacceptable. The acceptance of the message is a necessary precondition for the modification or change in existing attitudes or beliefs of the consumers.

• Retention: Retention means the storage and acceptance of the message in memory in such a way that it is accessible for future use.

External information sources can be categorized as (1) marketer-dominated and (2) non-marketer-dominated [BME01]. Marketer-dominated sources are provided by vendors for purposes of information and persuasion (e.g. advertising, web-sites, salespersons). However, non-marketer dominated sources like friends, families, opinion leaders and media may be even more influential to customers decisions than marketer-dominated information. By building virtual communities and employing recommender systems, vendors may utilize this kind of information to build credibility. For example, recommender systems may summarize community critique and recommend products with high ratings from the virtual community members or experts. By doing this, vendors may assist the consumer in the decision making process by providing nonmarketer-dominated information. However, in order to build or maintain credibility it is crucial to use this information sources honestly. For example if it turns out that a vendor manipulates or censors community opinions wrongfully, severe implications in regard to the credibility of the vendor may occur. Thus, a vendor should publicize codes of conduct or ethical guidelines, how he or she deals with information provided by customers or third parties in general.
In this context the question arises, how extensive consumers conduct external search. The framework of "economics of information" as proposed by Stigler [Sti61] provides an insight to this problem from a cost–benefit perspective. According to this framework consumers inform themselves about products and services on the market to the point where the marginal costs of gathering more information equals or exceeds the marginal return (i.e. the benefits from gathering new information) [Urb86]. A study conducted by Srinivasan and Ratchford identified perceived risk (i.e. the consumers' uncertainty about the potential positive and negative consequences of the purchase decision), amount of experience with the product class, content of experience (i.e. positive or negative), and cost of search as essential determinants of the amount of search effort [SR91]. Because online recommender systems can reduce search costs significantly, they are a valuable tool for consumers with respect to external search.
2.4.3 Pre-Purchase Evaluation of Alternatives

In this stage of the consumer decision process the focus is on the manner in which consumer evaluate purchase alternatives [BME01]. Before making a purchase decision, consumers usually compare and contrast different products and services. Consumers may use already existent or new evaluations stored in memory to select products and services that will most likely satisfy their needs. How this process is undertaken is again influenced by individual differences and environmental influences. In this process salient and determinant attributes are distinguished [BME01]. The consumers judge salient attributes as the most important characteristics of a product or service (e.g. price, processor speed and size of the hard-disk of a personal computer). However, the consumer applies determinant attributes to actually select a certain product and service, especially when the salient attributes are considered as equal between the alternatives. Determinant attributes turn out to be often very subjective to the personal taste of the consumer (e.g. design of the personal computer).

Figure 2.11 shows the pre-purchase evaluation process. When a decision has to be taken, consumers usually do not consider all available options. In fact they limit the alternatives to a subset called the “consideration set” [RL91]. When consumers are evaluating alternatives they may (1) rely on pre-existing evaluations stored in memory (in this case the consideration set is called the “retrieval set”) or (2) decide to construct new evaluations based on information acquired through internal or external search [BME01].

Pre-existing evaluations may be based on the consumers own past purchase and consumption experience with a product or service. In other cases – especially when the consumer has a lack of own experience – indirect or secondhand experiences (e.g. impressions heard from friends) may become dominant for the evaluation. This illustrates the importance of word-of-mouth in the decision process. When consumers are unable (e.g. lack of pre-existing experience) or unwilling (e.g. changes in environmental factors) to rely on pre-existing evaluations, they may decide to construct new evaluations. At this consumers may apply two basic processes: (1) the categorization process or (2) the piecemeal process [Suj85].

The categorization process refers to the evaluation of alternatives in respect of
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![Diagram of the pre-purchase evaluation process](image)

Figure 2.11: The pre-purchase evaluation process [BME01]

particular mental categories to which they are assigned. The basic assumption is that people naturally divide the world of objects around them in categories, permitting an efficient way of processing and understanding of the environment [Suj85]. These categories may range from very general (e.g. computing machines) to very specific (e.g. laptop computers from Apple). Consumers typically assign their mental categories some degrees of liking or disliking. Furthermore, the evaluation attributed to a specific category may be transferred to any new object of that specific category [BME01]. On a regular basis, this is how consumers form evaluations of new products and services. To the extent that the new products or services are assigned membership to a given category, they will be evaluated with respect to the degree of liking of that category. This process of retrieving evaluations can also be referred to as a “schema-driven affect”, because typical category “exemplars” or “prototypes” function as a scheme for the evaluation process [Suj85]. “Exemplars” are well-known actual examples of the category, whereas “prototypes” are abstract fictional images of the category, that embody typical attributes and characteristics associated with the category.
A more complex method to evaluate products and services is called the *piecemeal process* [BME01]. In this case, products are evaluated on an attribute-by-attribute basis. Products are perceived as a bundle of discrete attributes, with each attribute having a distinct subjective value or weight [Suj85]. The piecemeal process can be divided in three phases: (1) determination of important criteria or product dimensions, (2) judgement of the decision alternatives in view of each single attribute, (3) judgement of the overall performance of the alternatives.

In the first place, consumers must determine the *product dimensions* (e.g. processor speed, memory size, price of a personal computer), they want to employ in the evaluation-process. Further important dimensions are the feelings that come from owning and using a certain product (e.g. prestige, status, excitement). When decisions include "non-comparable" alternatives (e.g. a consumer has to choose between different product categories) more abstract criteria have to be employed, because the alternatives share only a few common criteria along which comparisons can be undertaken [Joh89, BS87]. For instance if a consumer has to decide between different forms of entertainment (e.g. buying a home stereo vs. buying a gaming console), more abstract criteria - like status or necessity - have to be used for comparisons.

The next step requires the consumer to evaluate each product and service in the consideration set along each criterion, that was judged as important before. As mentioned in Section 2.4.2, consumers perform internal (i.e. information already stored in memory) and external search to evaluate alternatives [SR91]. So called "cutoffs" are often used by consumers to simplify decision making [KB87]. A cutoff represents a predetermined acceptable level for an attribute. For instance, if a price of a product exceeds a certain acceptable limit, the product will be eliminated from the consideration set. *Signals* are a further important component in evaluating product attributes. In general, signals are product attributes that consumers use to infer other product attributes (e.g. price as an indicator of high quality) [BME01, DMG91].

The third and final step in the piecemeal process is the judgement of the overall performance of the alternatives in the consideration set. Consequently, this is derived from the evaluation of the performance of the alternatives in respect of each attribute. Research literature has identified a number of ways
how consumers perform this task [EJW04, BME01]. In principle compensatory and noncompensatory evaluation strategies can be distinguished.

*Noncompensatory evaluation strategies* refer to an evaluation process, where a product's weakness on one attribute can not be compensated by its strong performance on other attributes [BME01]. Noncompensatory strategies are applied in different forms [BME01, EJW04, GW84]:

- **Lexicographic strategy:** According to this strategy products are compared on the most important attribute. The product that performs best in regard to the most important attribute is selected. If alternatives are judged as equally good on the most important attribute, they are judged on the second most important attribute. This process continues until a product is judged as superior compared to others.

- **Elimination by aspects strategy:** This strategy is closely related to the lexicographic approach. Consequently, the products are judged on the most important attribute. However, now the consumer uses cutoffs (e.g. price of the home stereo must be below 500 €) for the determination of the alternatives. If only one alternative satisfies the cutoff on the most important attribute, the consumer chooses this product. If several alternatives meet the cutoff, the process continues on the second most important attribute and so on. If none of the products satisfies the requirements in respect of the chosen cutoffs, the consumer must revise the cutoffs, apply a different evaluation strategy or postpone the decision.

- **Conjunctive strategy:** In this strategy consumers also use cutoffs for the decision process. The consumer is required to set up minimum cutoff levels on each salient attribute. The products are compared one by one against this whole set of cutoffs. The product, that meets all of the cutoffs, is chosen. Failure to meet the preset cutoff levels for any attribute leads to the rejection of the item. As with the elimination by aspects strategy, if none of the products is acceptable, the consumer must change the cutoffs, use a different evaluation strategy, or delay the decision.

*Compensatory evaluation strategies* occur, when the consumer accepts that poor ratings on some of the attributes may be offset by excellent ratings on
other attributes. Consequently a perceived weakness of an attribute (even the most important one) may be compensated by other attributes. *Simple additive* and *weighted additive* are prominent forms of compensatory evaluations strategies [BME01, AM87]:

- **Simple additive**: The consumer simply counts the number of times each alternative shows itself favorably compared to the others in terms of the salient attributes. The alternative with the most counts is chosen. Consumers apply this strategy, when the processing motivation or ability is limited.

- **Weighted additive**: This is a more complex form of the compensatory strategy. In this case the consumers use weights, that reflect the importance attached to each attribute. Consequently, this requires more mental processing capacity by the consumer.

Understanding these strategies is an important issue when designing a *recommender system*. These systems are also in need of an “evaluation strategy” to determine, how much a consumer will like a certain product. The methods of generating recommendations may range from very simple (e.g. non-personalized recommendations based on statistical summarization) to fairly complex (e.g. personalized recommendations). For a detailed description of these methods see Section 3.5. For instance, if personalized recommendations are generated by means of attribute-based filtering (see Section 3.5.2.4), evaluation strategies of consumers are closely related to the *classification algorithm* (i.e. the algorithm to estimate the degree of interest in the product or service). If the chosen classification algorithm mimics the evaluation strategy of the consumer successfully and explains these assumption transparently (for explanations in recommender systems see Section 3.2), the consumer is likely to accept the recommendation.

### 2.4.4 Purchase

The next two stages in the consumer decision process model are purchase and consumption. Figure 2.12 summarizes, how the stages one to four (i.e. need
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Figure 2.12: The consumer decisions process: Purchase[BME01]

recognition, search for information, pre-purchase evaluation, and purchase) of
the consumer decision process model fit together:

In the purchase decision process consumer decide: (1) whether to buy, (2)
when to buy, (3) what to buy, (4) where to buy, and (5) how to pay. At this
purchase decisions may occur in three different forms [BME01].

1. Fully planned purchase: A purchase is referred to as fully planned, when
both the product and the brand are chosen in advance [BME01]. Consequent-
ly the consumer focuses his attention toward a specific product or
service when interacting with the e-commerce application. In e-
commerce applications recommender systems may be used as a marketing
tactic to divert the consumers attention to other brands. For instance
products with similar characteristics but better margins of profit may
be presented to the consumer when he adds a product to the virtual
shopping basket. However, consumer may perceive this as disturbing, if
he thinks that this kind of recommendations simply favors the e–vendor. Consequently, these “substitutive” recommendations must also offer a benefit to the consumer (e.g. suggesting a special offer with a better price/performance ratio). A less intrusive option is to display complementary products to increase cross–sales. For instance, if the consumer buys a specific digital audio player, a docking station and a protective cover may be recommended to him.

2. Partially planned purchase: The consumer knows which kind of product he wants to buy, but the concrete selection of a specific product or brand is deferred until shopping [BME01]. This is the typical application model for recommender systems (for a detailed description of application models see Section 2.3). In this case the focus of recommender systems is to give an overview of the range of product and services available and help to find the appropriate alternative. For instance, a list of top–sellers (broad recommendation lists, see Section 2.3.1) may be presented to the consumer. Another possibility is to use recommender systems in the form of so–called “product finders” to assist the consumer in the decision process. Product finders enable the consumer to specify certain attributes a (usually complex) product must have or must not have. The products that do not meet this requirements are filtered out from the range of products. Figure 2.13 shows such a product finder for digital cameras. The user may specify attributes (e.g. price, weight, and resolution). Cameras are filtered out from the available options accordingly to these specifications. Product finders must not be confused with attribute–based filtering systems (see Section 3.5.2.4). Product finders are designed for the ad–hoc use and consequently do not implement long–term personalization strategies. The consumer usually specifies the attributes and their values by him–or herself. This requires basic knowledge of the meaning of attributes from the consumer. In contrast attribute–based filtering systems pursue a long–term personalization strategy. These systems try to infer relevant attributes and their values by learning from user–behavior. Hence, these systems are well-suited for products with repeat–buying patterns (e.g. books).

3. Unplanned purchase: Unplanned purchases occur, when both product type and specific product or brand are chosen spontaneously [BME01].
Recommender systems may also be used to support this *impulse buying behavior*. For instance if a consumer adds a CD of a certain artist to his virtual shopping basket, buying a printed biography of that artist may be suggested to him or her. Studies show that unplanned purchases play a major role in “real world shopping” trips. Consequently, recommender systems may function as a vehicle to gain extra revenues in e-commerce applications by supporting impulse buying behavior [SKR01].

### 2.4.5 Post-Purchase Processes

The post-consumption processes include consumption, post-consumption evaluation and divestment. *Consumption* refers to the usage of the purchased product and service. *Post-consumption evaluation* is a further fundamental part of the consumer decision process model. During and past the consumption consumers form evaluations in regard to the product and the consumption experience [BME01]. *Divestment* constitutes the final stage of the model. At this consumers may resell, dispose or recycle the product [BME01].
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Figure 2.14: Three types of consumption experiences [BME01]

Consumption is always connected to experiences, that can be categorized as (1) positive reinforcement, (2) negative reinforcement, and (3) punishment [BME01]. Figure 2.14 gives an overview about these three types of consumption experiences.

Positive reinforcement occurs when the consumer receives a positive outcome from the product usage. For instance, playing a thrilling video game or reading an interesting book is regularly connected to positive reinforcement. Negative reinforcement emerges, when the consumption of a product or service enables the consumer to avoid or minimize negative outcomes. Vaccination is a typical example for negative reinforcement, because it prevents from getting sick. The third type of consumption experience is referred to as punishment. Punishment happens when the consumer receives negative outcomes from the product usage (e.g. listening to a CD the consumer dislikes). If punishment is experienced, it is quite unlikely that repeat usage or repeat purchase will occur [BME01].
2.4. THE CONSUMER DECISION PROCESS

The confirmation or disconfirmation of expectations that carried the consumer into purchase and consumption is of further interest. These expectations have a massive influence on the post-consumption evaluation.

Post-consumption evaluations are formed during and after consumption. Post-consumption evaluations may resemble pre-purchase evaluations, especially when the consumer is satisfied with the product or service. In other cases, post-consumption evaluations may differ substantially from pre-purchase evaluations [BME01]. In this case, the product may either do not meet the user expectations or perform significantly better than expected (which is the less frequent case, because low pre-purchase expectations seldom result in purchases). Post-consumption evaluations are of great importance for companies. They (1) influence repeat buying behavior, (2) shape word-of-mouth communication, and (3) lead to complaints due to dissatisfaction.

Repeat buying behavior usually emerges, when the consumer is satisfied with products or services. Hence, positive post-consumption evaluations are crucial for retaining customers [BME01]. This is of major importance for companies, because it is much cheaper to retain old customers than to gain new ones [FW87]. Consequently, marketing concepts like relationship marketing or one-to-one marketing have emerged. This concepts put heavy emphasis on customer retention. Recommender systems may further contribute to the retention of customers in respect of e-vendors. If recommendations are perceived as useful, they represent a value-added service, that leads to higher customer satisfaction. Especially personalized recommendations that are based on a long-term learning relationship foster the relationship between customer and company. In this case, switching costs arise for the customer. These switching costs hinder the customer from easily moving to another e-vendor.

Word-of-mouth communication is a further consequence of post-consumption evaluations. It is a common activity, that consumers are discussing their consumption experiences with others. Usually word-of-mouth communication resembles the outcome of post-consumption evaluation. Hence, the favorability of word-of-mouth communications is directly linked to the favorability of the consumption experience [NG05, Ric83]. A company's ability to provide a satisfying consumption experience will affect its ability in retaining current customers as well as acquiring new ones [BME01]. In e-commerce applications,
word-of-mouth communication could be used for purposes of the vendor. In this connection, recommender systems in conjunction with virtual communities offer a way to use word-of-mouth communication for recommendation purposes, for building credibility and to distinguish the vendor from others. For instance, if recommendations are given, *customer comments and ratings* may be displayed to enrich the vendor’s product or service description. This helps to build trust in the e-vendor. Further, some recommendation methods (e.g., collaborative filtering) require ratings of customers to generate recommendations. If a vendor wants to employ these recommendation methods a lively virtual community is a must. Additionally, customer comments and ratings may assist to improve the mix of products and services offered to the customer by eliminating products that cause massive dissatisfaction. Clearly, dissatisfaction is also reflected by decreasing sales volumes in the long run. However, using customer comments and ratings enables the vendor to react faster to dissatisfaction. For manufacturers and service providers, customer comments and ratings are a valuable source of information for product or service improvements.

*Complaints* are a further consequence of dissatisfied customers. Companies should encourage customers to communicate complaints. Corrective actions to avoid or minimize future unhappiness can only be taken, if the company knows the reasons for dissatisfaction [BME01]. Hence, companies should make it as easy as possible for customers to file their complaints. A sincere and quick response to complaints may alleviate dissatisfaction and may even lead to stronger repurchase intentions [Gil82, BME01]. Additionally, enabling the customer to express his dissatisfaction leads to significantly less negative word-of-mouth [NG05]. As a consequence, e-vendors should support the submission and management of complaints in their e-commerce application.

### 2.5 Virtual Communities

Virtual communities are an important factor in e-commerce applications and recommender systems respectively. In general virtual communities are *social networks that use computer-mediated spaces* (e.g., the Internet) for communication [HA97, LVL03, And02, Koz99]. They offer a potential for an integration
2.5. VIRTUAL COMMUNITIES

of content and communication with an emphasis on member-generated content [HA97]. In virtual communities people (e.g. consumers) interact socially for mutual benefits [And02].

Virtual communities may be classified along the desire to meet four basic needs: (1) interest, (2) relationship, (3) fantasy, and (4) transaction [HA97]. Virtual communities of interest bring together people that share an interest and an expertise in a specific topic (e.g. music-lovers). Virtual communities of relationship consist of people who have similar experiences. The community enables them to come together and form meaningful relationships (e.g. people with a certain disease). Virtual communities of fantasy give people the opportunity to come together for entertainment purposes (e.g. role-playing gamers). Virtual communities of transaction have the purpose to connect people, who want to trade information, products and services (e.g. communities located at eBay or Amazon).

2.5.1 Characteristics and Benefits

For the scope of this book, virtual communities of transaction controlled by e-vendors are of special interest. In general, these virtual communities may be operated by vendors or manufacturers (i.e. “seller controlled”) or independent third parties (i.e. “neutral”). In B2B-environments communities of transaction may additionally be controlled by buyers.

Communities of transaction controlled by e-vendors share the following characteristics [HA97, SG00]:

- Commercial orientation: The operator’s objective is to earn a financial return either directly (e.g. member fees) or – more common – indirectly (e.g. cross-sales, competitive barriers).

- Distinctive focus: In general, communities have a distinctive focus, which makes it easier for members to understand what kind of resources they are likely to find there. E-vendor controlled communities of transaction regularly focus on the offered mix of products and services. The objective
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is to support the customer in the buying decision process by providing additional member-generated content.

- Appreciation of member-generated content: In addition to the content published by e-vendors, virtual communities provide environments for the generation and dissemination of member-generated content. This enables the members to compare and aggregate their experiences in respect of the offered products and services. This fuller range of information may result in better purchase decisions in regard to their specific needs.

- A trustworthy commercial and social environment.

- Mutual support and the means for the identification of individual member needs to be based on shared community knowledge.

Virtual community of transactions offers the following benefits to the operator (i.e. the e-vendor) [PR98, HA97]:

- Interaction between customers and the e-vendor is strengthened.

- Customer loyalty is increased by building social networks between the customers.

- Competitive barriers are formed.

- Application of relationship-marketing concepts is facilitated.

- Consumers’ comments and ratings may be used for recommendation purposes (e.g. collaborative-filtering, statistical summarization of consumer opinions).

- Purchase power is grouped in homogenous target groups.

- Greater ability to tailor and add value to existing products and services.
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2.5.2 Virtual Communities and Network Effects

Virtual communities are subject to positive network effects [Lie02, HA97]. A positive network effect means that the value of a virtual community grows with the number of its members. That circumstance may ultimately result in increasing returns for the operator of the community [HA97, Art96]. This is caused by a series of interacting and reinforcing virtuous cycles shown in Figure 2.15 [HA97, PR98].

As Figure 2.15 illustrates, the reinforcing virtuous loops refer to [HA97, PR98]:

- Member-generated content: The basic assumption is, that member-generated content is a key source of content attractiveness. That content instigates members to join and remain in a virtual community. As a consequence, the more members a community has, the more content is created. This in turn raises the attractiveness of the community, which causes more people to join the community.
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• Customer loyalty: The more members and content a community offers, the more it is likely that member will communicate with each other. This tightens the social network and leads to increased loyalty towards the community. Again this process is self-reinforcing and leads to an increase of community members.

• Member profiles: With growing numbers of community members the e-vendor may infer more explicit and implicit information about the customers. Consequently, the quality of recommendations based on collaborative filtering, product association rules and statistical summarization can be improved (for a description of these methods see Section 3.5). In addition other value-added services tailored to the individual customer may be offered. This augments the attractiveness of the offerings and will once again lead to an increase of community members.

• Transactions: A large community reflects a high number of (potential) buyers. This increases the transaction volume and market power of the e-vendor respectively. Hence, the e-vendor may bargain better conditions for purchasing from wholesalers and manufactures. These improvements (e.g. price-discounts) may be passed on to the customers. A further possibility to employ the dynamics of the transaction loop is to integrate consumer-to-consumer business models in the e-commerce retailing application. For instance, Amazon.com acts as a market-maker (i.e. broker) for used books. Customers may sell their used-books on Amazon. The larger the community is, the more potential buyers and sellers are in the community. Again, this makes the community more attractive. Hence, the e-vendor may extend the existing revenue model by charging transaction fees for the brokerage service.

As a result from these self-reinforcing cycles, managing member evolution is a key success factor of virtual communities [HA97, PR98, And01]. When a critical mass of members is reached, network effects lead to a self-reinforcing growth of contents, member profiles, loyalty and transactions. In the following chapter problems related to the successful building of a virtual community is discussed.
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2.5.3 Community Building

One of the most challenging problems of setting up a virtual community is to achieve a critical mass of members. Hence, e-vendors should assess their potential to control a community carefully [And01, HA97]. The potential of a successful community depends on (1) indicators of the economic potential and (2) resources of the community organizer [HA97].

*Indicators of the economic potential* include (1) the size of the potential community, (2) the relative value of being online, (3) the value of being in a community, (4) the likely intensity of e-commerce, (5) the fractal depth of the community, and (6) the fractal width of the community [HA97].

Estimating the potential size of the virtual community can be done by referring to demographic statics. For instance, a book-seller may focus on a specific area (e.g. German-speaking countries). Another factor that is of interest is the spending information of the individual consumers. Spending information helps to assess the overall market size in terms of money and potential sales volume for the e-vendor. A further determinant of the potential size of the community is the number of people buying information about the specific field of interest. For instance, how many people do subscribe to music-related journals or magazines? Answering this question may help to determine the relevancy of a virtual community for these people. Another factor that may help to estimate the size of the community can be membership in associations or groups. This factor clearly shows the importance of social networks in the relevant field [HA97].

Firstly, the *relative value of being online* refers to the number of people, who have the ability to join a virtual community because of their physical equipment to go online. For instance, a virtual community for well-educated and middle-aged people is more likely to be successful compared to communities who aim at elderly and poor people. The second aspect is the relative value of the online-community compared to off-line alternatives. If the virtual community is cheaper, more efficient and offers unique capabilities it is likely to prosper. For instance many online newspapers or magazines add the ability to comment articles by community members. This creates an added service because people are often interested in the opinion of others. This service
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offers a chance to discuss with like-minded persons and to form social networks with them. Further, the relative value of virtual communities that focus on markets that are fragmented or where geography creates barriers is regularly very high [HA97]. For instance, communities of transaction that focus on spare parts for rare old-timer cars may be successful because of this.

The value of being in a virtual community refers to the intensity of satisfying needs [HA97]. In community of transactions these needs are usually related to the products and services the community focuses at. If the products are complex, hard to evaluate and complicated to use (e.g. sophisticated software) it is very likely that the virtual community assists the members in solving product-related problems. Here, experiences of other purchasers of the same goods constitute a valuable source of information.

Especially in virtual communities of transaction the likely intensity of e-commerce is of major interest. The operator of such a community must estimate the overall volume of transactions conducted by the targeted community group and the average size of each transaction [HA97]. In this context, characteristics of the products and services (e.g. size and bulk relative to value, thin markets, perishability, immediate gratification factor) offered by the e-vendor are of major importance. For a discussion of products that are likely to create a large transaction volume by e-commerce applications see: [HN05, Lie02]

The fractal depth of the community is the degree to which it can be segmented into sub-communities. The more ways a community can be split, the more it can create small and focused sub-communities. In these sub-communities the participants are more likely to have common interests. As a consequence, the members will be more dedicated to the sub-community and spend more time online. Further, members are more likely to engage in transactions [HA97]. For instance, a travel community can be split by regions, by travel type (e.g. air travel, train journeys), and by reasons for travel.

Fractal breadth of the community refers to the ability of the community to build out to arenas that bear no relation to the community’s original focus [HA97]. This may enable the e-vendor to extend the offered range of products and services. For instance, a book-seller with a lively community may have an advantage, if the vendor decides to offer CDs additionally. It is likely that
synergy effects will occur, because community members will also engage in rating CDs and making comments on them.

Besides the indicators of the economic potential mentioned above, the following resources of the e-vendor ease the building of a community especially in the early stages: (1) brands, (2) customer relationships, and (3) content.

A strong brand carried over to the online world is a valuable asset for attracting customers to a web-site. Brands help to establish trust and credibility especially in the early stages of the community. Hence, brands make it easier to reach a critical mass of community members and to set the reinforcing virtuous cycles into motion [HA97].

Established customer relationships are a further benefit in the early stages of community building. Customer relationships can be understood as strong understanding of what the individual customer wants and an ability to deliver what the customer needs. They also imply an ongoing interaction with customers that constitutes an opportunity to introduce them to a newly established virtual community [HA97]. Regarding the ongoing interaction necessary for customer relationships, virtual communities may also help to reduce transaction costs for both the e-vendor and the customer since online communication is regularly cheaper.

Published content is a further key factor in the early stages of virtual communities. Since the volume of member-generated content is low in these stages, providing an interesting content is helpful to attract members, particularly if the content is adapted to make use of the special capabilities of the online medium [HA97]. For instance, a book-seller may buy in book-reviews from external sources. These reviews from experts may spur community member to post their own opinions in the virtual community.

In the context of community building the typical member development path is of special interest. Figure 2.16 exhibits the four stages of member development.

The first step is to attract members. Marketing initiatives, attractive content, and free membership and usage are levers to allure new members to
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Figure 2.16: Four stages of member development (adapted from [HA97])

Attract Members
- Marketing
- Attractive Content
- Free Membership and Usage

Promote Participation
- Engaging Member-Generated Content
- Editorial/Published Content
- Guest Speakers

Build Loyalty
- Member-to-Member Relationships
- Member-to-Host Relationships
- Customized Interaction

Capture Value
- Transaction Opportunities
- Recommendations
- Fees for Premium Services

For community building purposes it is of importance to understand that not all community members are equal in terms of their economic potential to the community [HA97, Koz99]. Figure 2.17 presents a classification of different types of members in communities of transaction [Koz99].

The formation of lasting identification as a member of a virtual community is largely determined by two factors: (1) the self-centrality of the consumption activity and (2) the intensity of the social relationships the person possesses with other members of the virtual community [Koz99]. The concept of self-centrality of the consumption activity refers to the importance of the symbols of the particular consumption in respect of the self-image of a person [Koz99]. For example, for book-aficionados reading books is a central activity to their psychological self-concept. The higher the self-centrality of the consumption activity the more likely a person will be to pursue and value membership in a virtual community. The second factor, social ties to the community is very often related to the self-centrality of the consumption experience. For
instance, a young male who is extremely devoted to classic Italian scooters and who lives in a rural environment is likely to seek like-minded people on the Internet, especially if he has few people in his face-to-face community that share his passion.

As shown in Figure 2.17 **tourists** lack strong social ties and their interest in the consumption activity is only superficial or passing. Consequently, the interest in the products and services offered is very limited. **Minglers** are persons that maintain strong social ties, but show no deeper interest in the central consumption activity. In contrast devotees maintain a strong interest in and enthusiasm for the consumption activity. However, their ties to the virtual communities are low. The last category is called the **insider**. Insiders show strong interest in the consumption activity and have strong personal ties to the community [Koz99].

From a marketing perspective **devotees and insiders** are the most important target group for communities of transaction. Because of their high self-centrality of consumption, these two types usually are “heavy users” of the offered
products and services of the e-vendor. Thus, they will have a large share of transactions and sales volume respectively, especially when repeat-purchases are characteristic for the offered product category (e.g. books, CDs). Additionally, devotees and insiders regularly have a massive knowledge of consumption. This makes them a primary target for the contribution of member-generated content. In this context personalized recommendations are a good initiative to tie devotees to the community and convert them to “loyal” insiders, because of switching costs.

To get a better understanding of the interests of the different types of community members, different social interactions modes are presented in Figure 2.18. As a consequence, community organizers may apply interaction-based segmentation for the separate groups. This will allow community organizers to better formulate strategies that recognize the differential opportunities and needs of devotees, insiders, minglers and tourists [Koz99].

As shown in the figure, the modes of interaction are classified along two criteria: (1) objective of communication and (2) orientation of the communication. The objective of communication may be autotelic or instrumental. Autotelic communication takes place for the sake of its own (i.e. it has an end in itself), whereas instrumental communication is used to as a means for the accomplishment of other ends [Koz99].

In general devotees and tourists are uninterested in building online social ties. In virtual communities these member-types tend to use the informational mode of interaction. They primarily use online communication as a means for the accomplishment of specific goals (e.g. improve the quality of their purchase decision by reading comments on products and services of other community members). The social orientation of their communication is individualistic. These two groups usually communicate in order to receive a short-term personal gain. In general they are using other community members resources and do not intend to returning anything of benefit to other individuals or the group as a whole [Koz99].

In the context of recommendation applications devotees and tourists try to benefit from recommendations. In general they are not prepared to make an effort by themselves by rating or commenting products and services (i.e
“free-riding”). Hence, explicit methods of data acquirement are not suitable for these groups (for a detailed description of methods of data acquirement see Section 3.1). However, they may be a valuable source of information, if implicit methods are used (e.g. click-stream analysis). Additionally, e-vendors should encourage devotees to share their knowledge of products and services by applying marketing initiatives (e.g. incentive programs). Because devotees and tourists pursue short-term goals, personalization strategies may not be applicable. Thence, non-personalized recommendations should be applied.

*Minglers and insiders* are usually far more social in their group communication behavior. As a consequence they often use the *relational interaction mode*. To them, the social contact in the virtual community has a value in its own. Their focus is on long-term personal gain through cooperation with other community members or the delineation and enforcement of communal standards [Koz99]. This makes this interaction mode the most valuable for recommendation applications. Clearly, insiders and minglers are a valuable source for member-generated content. Especially insiders are the primary tar-
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get group for the provision of ratings and comments, because of their usually high level of product-related knowledge.

The *recreational mode* refers to interactions that are conducted for primarily selfish or short-term satisfaction. In this mode online communication itself is the goal. It mainly occurs, when synchronous communication is possible in the virtual community (e.g. chat rooms). A good example is the often insipid small talk in chat rooms. This form of interaction is mainly used by *tourists and minglers* [Koz99].

*Transformational interaction* occurs when community members strive for positive change in regard to their interests. It is focused on longer-term social gain. This mode of interaction is primarily used by *insiders and devotees* [Koz99]. The goals connected with this interaction mode may sometimes be antipodal to the interests of the e–vendor (e.g. empowerment of consumers, change in consumption behavior).