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Nicolas Knotzer

Product Recommendations in E-Commerce Retailing Applications

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The book deals with product recommendations generated by information systems referred to as recommender systems. Recommender systems assist consumers in making product choices by providing recommendations of the range of products and services offered in an online purchase environment. The quantitative research study investigates the influence of psychographic and sociodemographic determinants on the interest of consumers in personalized online book recommendations. The author presents new findings regarding the interest in recommendations, importance of product reviews for the decision process, motives for submitting ratings as well as comments, and the delivery of recommendations. The results show that opinion seeking, opinion leading, domain specific innovativeness, online shopping experience, and age are important factors in respect of the interest in personalized recommendations.

Nicolas Knotzer studied business administration with the focus on information systems, management control and project management. From 2001 to 2006 he joined the Institute for Management Information Systems at the Vienna University of Economics and Business Administration. The author received his doctoral degree in 2006.

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Abstract

The book deals with product recommendations generated by information systems referred to as recommender systems. Recommender systems assist consumers in making product choices by providing recommendations of the range of products and services offered in an online purchase environment. The quantitative research study investigates the influence of psychographic and sociodemographic determinants on the interest of consumers in personalized online book recommendations. The book starts with an introductory chapter that sets out the research goal and presents the organization of the work. In Chapter 2 the author establishes working definitions, introduces a general classification and presents application models and business goals of recommender systems. Further, a model of the consumer decision process and the relevancy of virtual communities for recommendation purposes is described. Chapter 3 reviews functional aspects of recommender systems. Input and output data, measurement scales for preference elicitation as well as recommendation methods are elaborated in detail. Chapter 4 describes the research model, the hypothesis, and the methodology. The results of the empirical study are presented in Chapter 5. Structural equation modeling and regression analysis are used to verify the hypotheses. The author presents new findings regarding the interest in recommendations, importance of product reviews for the decision process, motives for submitting ratings and comments, and the delivery of recommendations. In particular the results show that opinion seeking, opinion leading, domain specific innovativeness, online shopping experience, and age are important factors in respect of the interest in online recommendations. The book closes with an chapter that summarizes the results, shows limitations of the research conducted, and points out directions for further research.

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Chapter 1

Introduction

Information systems that *assist consumers in the buying decision process* are recognized to be one of the most promising appliances in e–commerce environments [SP02, SV99]. In this context *recommender systems* support the consumer in this process by providing *recommendations* of products and services to help customers find products to purchase [SKR01]. Recommender systems aid the consumer by reducing information overload, providing personalized product information, ranking products according to the individual user's preferences, providing community critiques, and summarizing community opinion [Run00]. Hence, recommender systems represent interesting opportunities for e–commerce vendors to deliver value–added services to the customer. Recommender systems ideally assist e–commerce vendors 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].

1.1 Research Goal

The majority of research literature regarding recommender systems deals with this topic from the viewpoint of computer science. The focus is on the underlying algorithms for generating recommendations [KSS03, SKKR00, BS97, Bur02, SVA97, Run00]. The existing research in respect of the marketing perspective (e.g. the influence of recommendations on consumers decisions) is still scarce [SN04, HK04, HM03, CLA+03, HT00]. Therefore, the author has decided to address the research field "recommender systems" from a marketing perspective.

As examined by Katz and Lazarsfeld in their classic article "Personal Influence: The Part Played by People in the Flow of Mass Communications" interpersonal communication (i.e. "word–of–mouth") is a very important factor in the buying decision process [KL55]. By providing community critiques and summarizing community opinion, recommender systems may be used to facilitate interpersonal communication between customers. In this context, the question arises which psychographic and sociographic factors determine the interest in recommendations as well as the interest in word–of–mouth.

Thus, the thesis strives to *identify the underlying psychographic and sociodemographic determinants* that define: (1) the consumer's interest in *personalized recommendations*, (2) the consumer's interest in participating actively in virtual communities of transaction located at online purchase environments by *submitting product–related ratings and comments*, and (3) the consumer's interest in *product–related opinions of other consumers* in virtual communities.

The author tries to address this question in the context of online book recommendations. This product class was chosen for the following reasons:

- Books are the most prominent product category sold over the Internet worldwide and in Austria [AIM05]. Hence, it is more likely that participants of a survey with respect to book recommendations have experience in this context, which makes the results of the survey more reliable.
- Books are a product class where subjective tastes and preferences are of high importance for the buying decision. As a consequence, word–of–mouth and virtual communities are important facets in this product category.
- Selling books over the Internet is a typical application domain for recommender systems based on collaborative filtering or summarization of community opinion.

Further, the following research topics are addressed by means of exploratory research:

- Recommendations and impulse buying behavior.
- Importance of ratings and comments from different sources for the decision process.
- Motives for submitting ratings and comments to virtual communities.
- Benefits of recommendations from the consumer's perspective.
- Privacy issues in the context of implicit data acquirement for preference elicitation.
- Communication methods for the delivery of recommendations.

In the thesis, a quantitative approach for the examination of the research questions is applied. Consumers were asked to answer a standardized web-based questionnaire regarding recommendations and product-related word-of-mouth. The research model is verified by the application of *structural equation modeling* and *regression analysis*.

1.2 Contents and Organization

This doctoral dissertation is divided into *six chapters* that review relevant marketing and computer science literature, introduce the underlying theory and hypotheses, describe the study methodology, and present the results as well as conclusions, implications and limitations.

In the following chapter, recommender systems are examined from a *marketing perspective*. At first, the working definitions of the thesis and a taxonomy of recommender systems are established. The next section takes a look at business goals of recommender systems and introduces the corresponding application models. The following section deals with the consumer decision process and how this process may be influenced by recommender systems.

In the last section of Chapter 2 virtual communities and their relevancy for recommendation purposes are addressed.

Chapter 3 reviews *functional aspects* of recommender systems. In the first section of the chapter, input and output data of recommender systems are illustrated. Further, approaches to provide supplementary explanations (i.e. why certain products are recommended) are investigated. In the next section, different *statistical measurement scales* for the elicitation of preferences are introduced. Additionally, the information delivery aspects of recommender systems are highlighted. The chapter concludes with a section that gives a detailed review of recommendation methods and their corresponding advantages and disadvantages.

Chapter 4 deals with the research model, the hypothesis and the methodology of the thesis. In this connection, the problem statement of the thesis is elaborated and the research questions are introduced. Furthermore, the underlying theoretical framework and the hypothesis derived from the research questions and the framework are described. The final section of this chapter focuses on the methodological aspects of the thesis and introduces the research design.

In Chapter 5 the results of the study are set out. In the first step, the descriptive results are presented (i.e. results that are not related to the hypotheses and the research model respectively). In the next section the verification of the research model is conducted. This section is structured in three parts: (1) hypotheses regarding psychographic factors that are verified using structural equation modeling, (2) hypotheses regarding psychographic factors that are scrutinized using a regression model, and (3) demographic hypotheses.

Chapter 6 reviews the dissertation's implications and limitations. In addition, directions for further research are outlined.

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 relevancy 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:

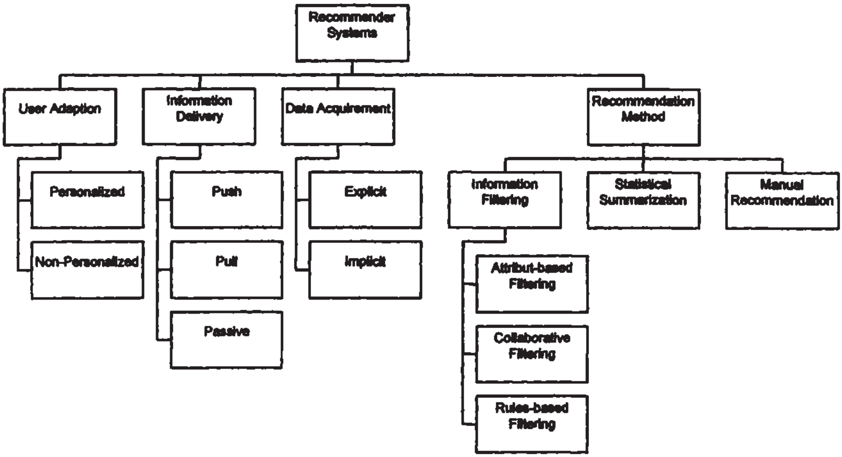


Figure 2.1: Classification of recommender systems

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-

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.

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.

Application Model	**E-Commerce Business Goal**
Persistent personalization	Building long term relationships
Product associated recommendations	Cross-selling
Notification services	Inviting customers back
Customer comments and ratings	Building credibility through community
Broad recommendation lists	Turning new and infrequent visitors into buyers

Degree of personalization

Figure 2.2: Overview of application models and e-commerce business goals

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 [SKR01].

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].

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.

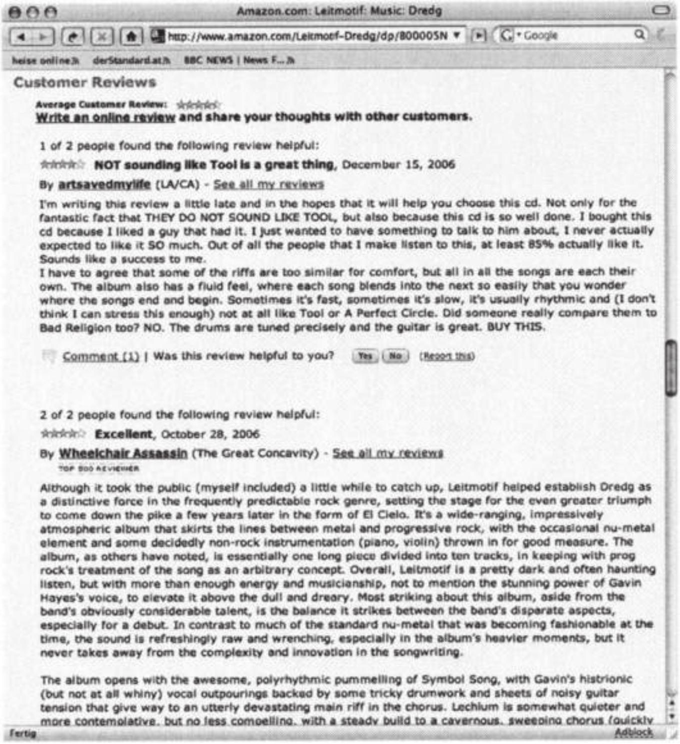


Figure 2.4: Customer comments and ratings on CDs at Amazon.com

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.* 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

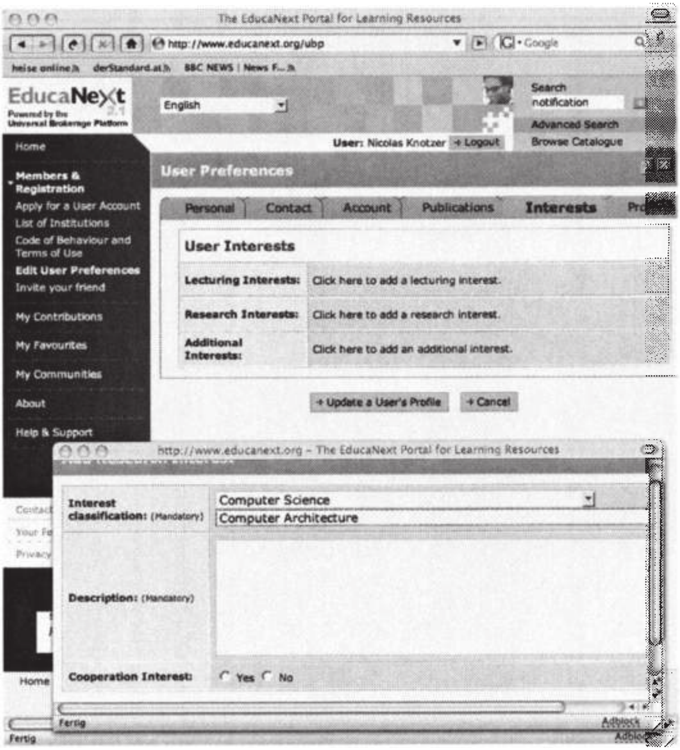


Figure 2.5: Notification service of Educanext.org

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-

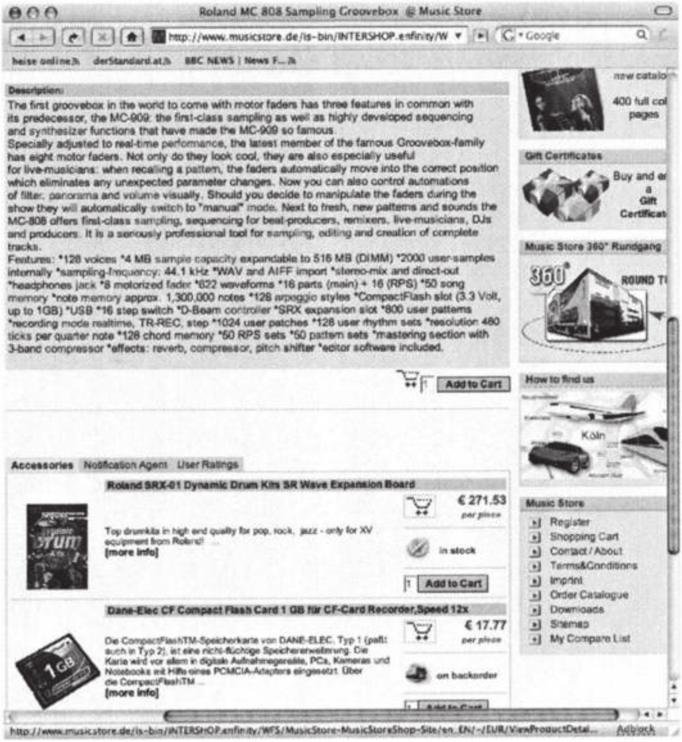


Figure 2.6: Cross–selling based on product attributes at Musicstore.de

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).

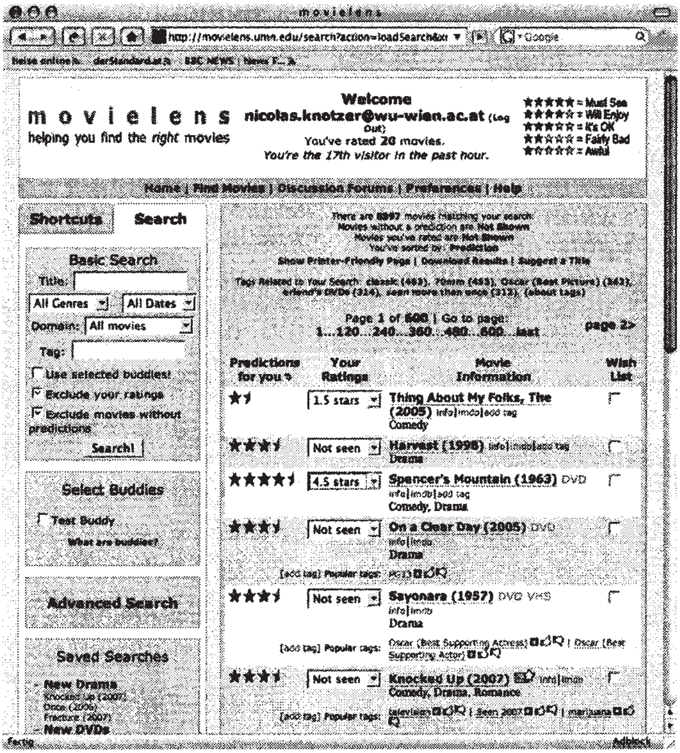


Figure 2.7: Persistent personalization based on collaborative filtering at Movielens.emu.edu

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

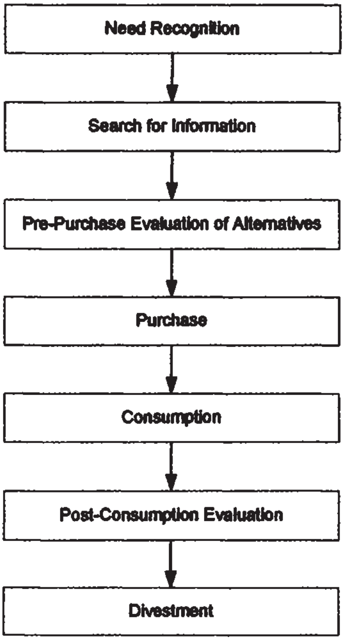


Figure 2.8: The consumer decision process[BME01]

method to effectively make customers aware of their desire. The needs of customers are essentially influenced by two factors: (1) *environmental influences* (e.g. culture, social class, personal influences) and (2) *individual differences* (e.g. consumer resources, motivation, attitudes, knowledge) [BME01]. If recommendations take these two factors into consideration, they may effectively assist the consumer in identifying his needs.

2.4.2 Information Search

Information search is the next step in the consumer decision process model. Once a need is recognized, consumers starts 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-

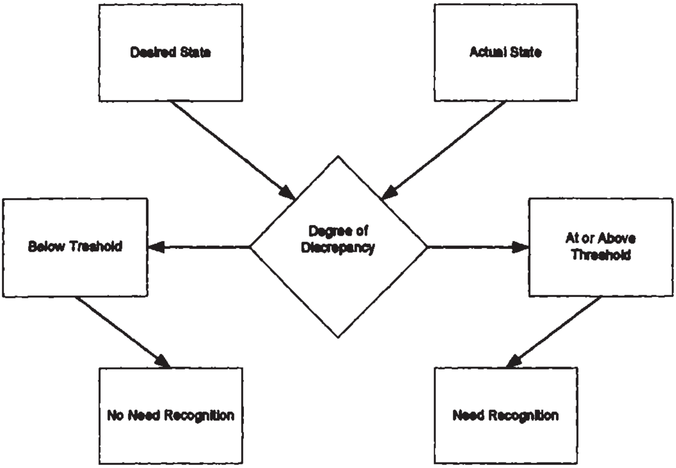


Figure 2.9: The need recognition process[BME01]

ternal 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]:

- 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 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.

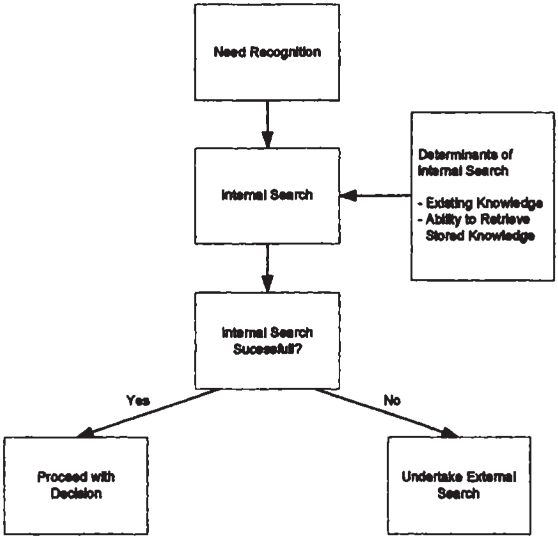


Figure 2.10: The internal information search process[BME01]

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 the 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

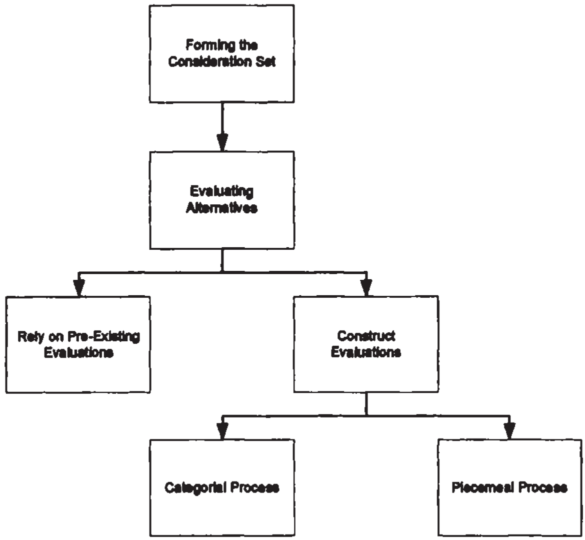


Figure 2.11: The pre–purchase evaluation process[BME01]

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 a 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

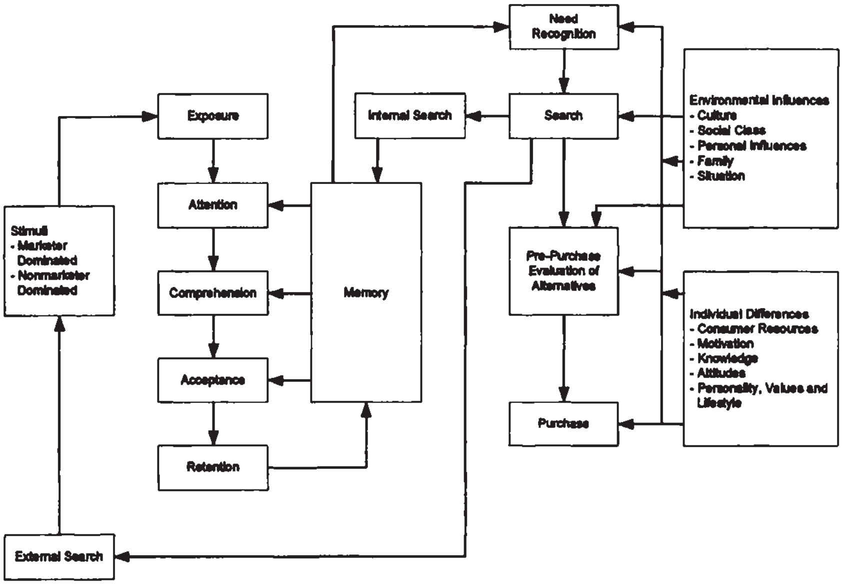


Figure 2.12: The consumer decisions process: Purchase[BME01]

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]. Consequently 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].

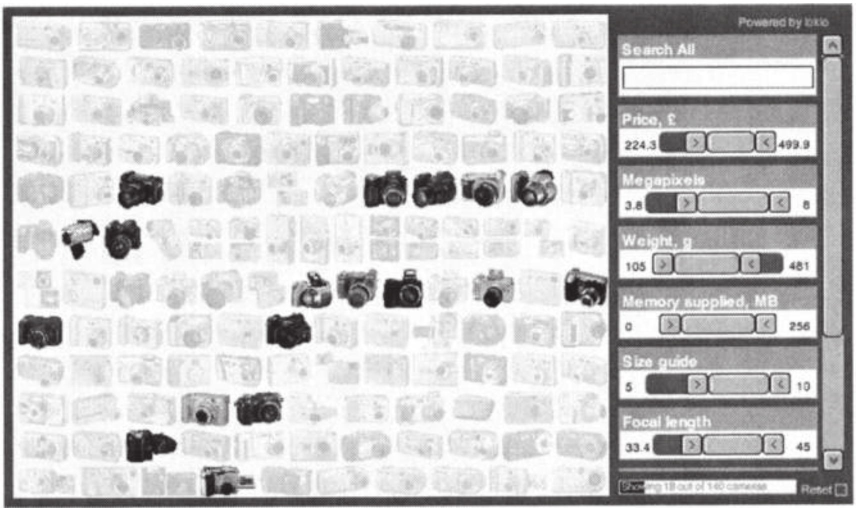


Figure 2.13: A product finder for digital cameras

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].

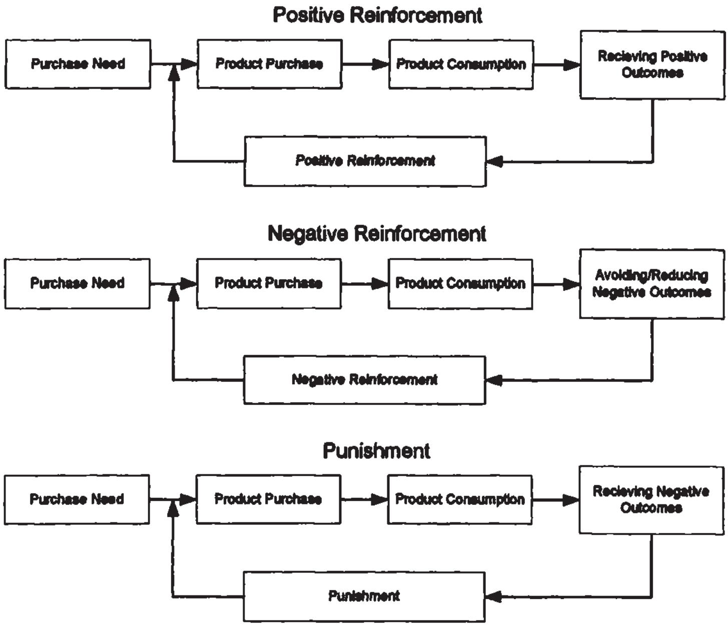


Figure 2.14: Three types of consumption experiences [BME01]

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].

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 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

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.

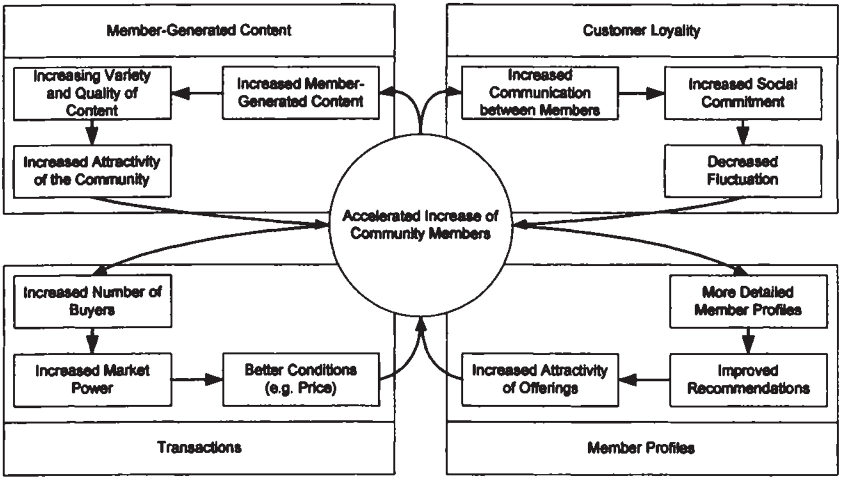


Figure 2.15: Reinforcing virtuous cycles in e–vendor controlled virtual communities of transaction (adapted from Paul and Runte [PR98])

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.

- 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.

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 asses 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 questions 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 to ability to join a virtual community because of they are physically equipped 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 value–added service because people are often interested in the opinion of others. This service 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, particulary 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

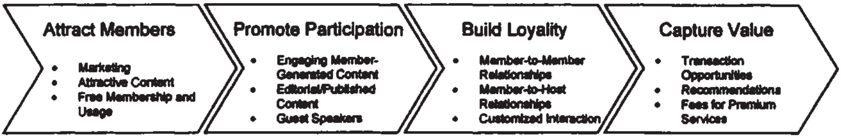


Figure 2.16: Four stages of member development (adapted from [HA97])

the community. The next stage is to *promote participation* in the community. For instance, community organizers should provide incentives to engage community members in providing member–generated content. In the following *building loyalty* is of central importance for community operators. Loyalty emerges by supporting member–to–member relationships and by fostering member–to–host relationships. For instance, existing customer retention strategies should be incorporated and adapted to the enhanced possibilities of the online medium. Finally, the e–vendor should *capture value* from the community engagement. Recommendations based on member–generated content (i.e. collaborative filtering, product–association rules, statistical summarization of community opinions) may be applied to increase transaction opportunities. A further possibility to capture value is to offer individualized products and services based on the information stored in the member profile [SG00].

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

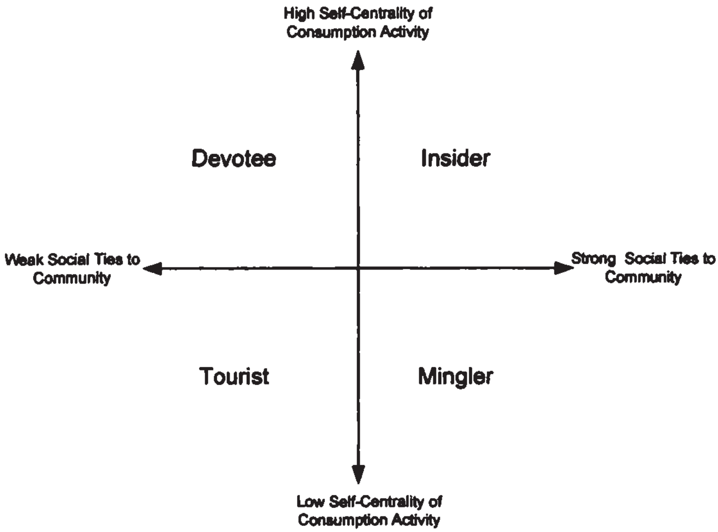


Figure 2.17: Types of virtual community members [Koz99]

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

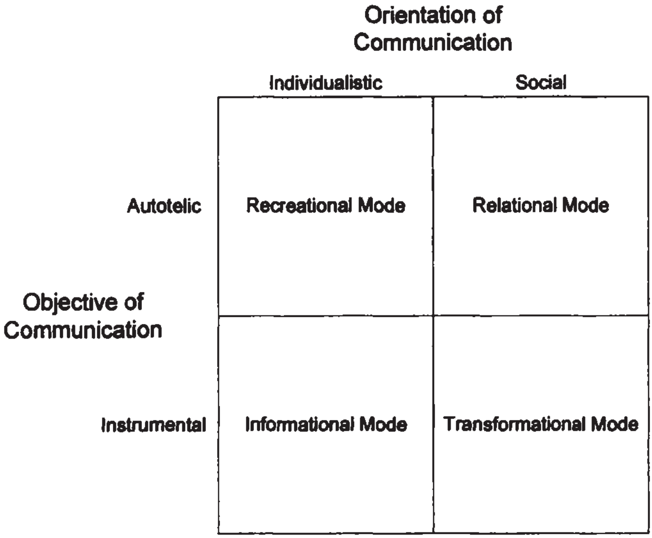


Figure 2.18: Interaction modes in virtual communities of transaction [Koz99]

"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 target 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).

Chapter 3

Recommender Systems – Functional Perspectives

This chapter gives an overlook of the functional aspects of recommender systems. It deals with functional input and output of recommender systems, measurement scales for preference elicitation, information delivery aspects, and recommendation methods.

Input data of recommender systems are described in Section 3.1. Input data can be classified along the dimensions *duration, acquisition, originator and origin.*

Section 3.2 deals with output data of recommender systems. Besides the recommendations itself, recommender systems may display *predictions, text comments and ratings* to the user. Further, possible approaches to provide supplementary *explanations* (i.e why certain products are recommended) are presented. Finally, the basic flow of input and output data in e–commerce recommendation applications is illustrated.

Section 3.3 examines different *statistical measurement scales.* It focuses on metric scales for the elicitation of user preferences.

Section 3.4 refers to the information delivery of recommender systems. *Push, pull and passive* technologies may be used to suggestions, ratings and predictions to the user. Push, pull and passive technologies refer to the extent of the user's initiative to get recommendations.

The chapter concludes with the introduction of different recommendation methods. *Personalized and non-personalized recommendation methods* and their corresponding advantages and disadvantages are described in detail.

3.1 Input Data of Recommender Systems

This section deals with the functional input data of recommender systems. Recommender systems use input data to generate output in form of suggestions, predictions and ratings. Figure 3.1 illustrates a classification scheme for input data of recommender systems.

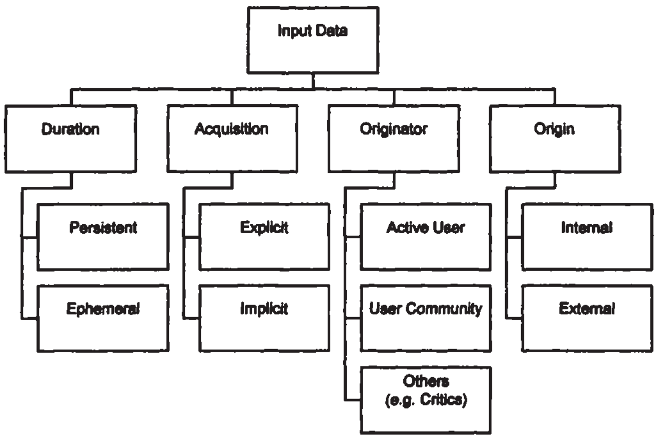


Figure 3.1: Classification of input data

Depending on duration of the user data storage, persistent data, ephemeral data, or a combination of both may be used for personalized recommendations [MT02]. *Ephemeral data* is used on a per session basis only and is deleted afterwards, whereas persistent input data is stored over different user interaction sessions. Thus, ephemeral personalization can be applied to users, who are not authenticated to the e–commerce application. It may be useful when users are new or are reluctant to give personal information to the e–vendor. For instance, the current navigation of an unregistered (i.e anonymous) user could be used to push recommendations based on that context. *Persistent data* is acquired over different sessions and stored in user profiles permanently. Thus persistent data storage allows improving the user–profile over time and collecting long–term preferences of the users of the e–commerce application.

Acquisition denotes how the input data is gathered from user interaction. *Explicit data* is intentionally submitted by the user to inform the recommender systems about his preferences (e.g. rating items on a nominal scale), whereas *implicit data* stems from monitoring user behavior (e.g. browsing the product catalogue) [SKR01]. In this context data acquisition is related to user awareness. This denotes the extent to which the user is required to give inputs to the recommender system intentionally. Consequently user awareness refers to the user's state of mind while interacting with the e–commerce application.

The advantage of explicit approaches is that the users know their interest best and are in control of the recommendation process. However, explicit approaches put the effort of adapting recommendations towards the users. Further, the users have to learn to handle the input forms of the recommender system. Thence, complexity is increased from the users' point of view. Consequently the user–interfaces of recommender systems, which are operated by non–specialists per definition, have to be designed carefully in respect of usability.

The pros of implicit approaches are that no or little effort is put towards the users and that no special knowledge of the user is required. But the user loses control over the recommendation process. Further implicit approaches reduce transparency of recommendations, i.e. the user does not understand how recommendations are generated. Thus it is difficult for the user to develop a coherent cognitive model of the recommender system [Wae04].

User interrogation is the most commonly used explicit data acquisition approach. The user is required to fill out forms to describe interests or other relevant parameters (e.g. keywords and attributes of items). User interrogation is often applied to obtain ratings of items the user has already knowledge of. These ratings may be based on an ordinal scale (e.g. "rate this item on a scale from one to five") or on a binary scale (e.g. "do you like this item - yes or no").

Recording user behavior is an typical implicit approach. It does not require the user to intentionally engage in the data acquisition process. A simple approach would be to give recommendations based on the item the user is currently viewing. In e–commerce applications the articles in the virtual shopping–basket, the articles bought in the past or other clickstream–data can be utilized for recommendation purposes. According to studies from Morita and Shinoda as well as Konstan et al. the time a user spends viewing an artefact is a appropriate indicator for the relevance to the user [MS94, KMM+97]. Hence, time spent to view articles can be used as implicit input data for recommendations, although this data may be biased (e.g. the user is interrupted).

Explicit and implicit approaches may be combined. Usually these combined methods use explicit approaches to gain knowledge about the user in the initial phase of the system use and change over to explicit approaches in later phases. For instance reference items can be used to create an initial *item space* (also referred to as *document space* because this method was first applied on textual documents [FD92]). The user has to judge the relevancy of these reference items by explicit user interrogation. New items are compared to these reference items and are recommended if the similarity to these reference items, which were rated as relevant, exceeds a certain threshold. The advantage of this method is, that the effort of user interrogations is limited to the initial system use. However, from the user's point of view it is hard to estimate the usefulness in the beginning of the system use. Hence, he or she might not be willing to put effort into judging reference items, when he or she has little knowledge about the advantages of using the system. Additionally ongoing bias of the users interests may occur, if certain areas of interests are not covered by the initial item space [HSS01]. *Stereotypic inference* is another combined approach. A Stereotype is a collection of attributes that often cooccur in people, i.e stereotypes are typical characteristics of user groups in a given domain [Ric89]. Users are asked to provide personal information by explicit approaches in the initial phase of system use. These data is used to relate the user to a specific stereotype (i.e. default initial profile) [HSS01].

This method helps to address the bootstrapping problem (i.e. giving suitable recommendations to new users). Consequently, stereotypes enable the recommender system to make plausible inferences on the basis of a substantially smaller number of observations of the user's behavior. Over time observations are added to the profile, which may enhance or override default assumptions about the user.

A further criterion to classify input data of recommender systems is the originator of the input data, whereby active user input, community input and input from others (e.g. editors, critics) can be distinguished.

Active user input refers to the data generated through interactions with the active user (i.e. the user who currently gets recommendations). Active user data typically include:

- Session information (e.g. log–in and log–out times, session–identification numbers, navigational–data)
- Buying behavior (e.g. items in the virtual shopping–basket, items bought or consumed in the past)
- Search behavior (e.g. keywords, queries)
- Transactional information (e.g. forms of payment, account numbers, shipping address)
- Preferences (e.g. expressed preferences, implicit preferences)
- Individual characteristics (e.g. demographic data)

Community inputs usually refer to the sum of all active user inputs. Besides those internal data (see below) community inputs may also include external data (e.g. item popularity in form of national best–seller lists). Generally spoken, community inputs comprise of data, which denotes how multiple individuals in the community or the community as a whole perceive attributes of items (e.g. book categories or film genres are derived from the consensus of the broader society) [SKR01].

Text comments are community inputs in form of textual descriptions of users' experiences with single products or services. Text comments may be very useful to enhance the decision making process of the active user. However, the user's effort of processing text comments fairly high, since the user must read this textual information and interpret to what degree these comments contain positive and negative attitudes toward the item.

To ease this procedure, textual comments are often supplemented by *scores or ratings* of users, which indicate the overall satisfaction with the item. Additionally, these individual ratings can be summarized (e.g. by calculating the arithmetic mean) to get an quick overview of the users' average opinion.

Finally, depending on the source, input data can be classified into internal and external data. *External data* stem from third parties and may relate to items or users. For instance item–specific external data may be derived from third party electronic product catalogues with categorizations and descriptions of product attributes (e.g. genre and keyword classifications of books or films) [SKR01]. External item popularity (e.g. national best–seller list) is a further example for item–specific external data used for recommendation purposes. Typical user–specific external data stem from market research companies (e.g. general demographic data of online-shoppers) and may also be used in the recommendation process. In contrast to external data *internal data* is exclusive to the e–commerce vendor. Thus, it is of major importance in regard to competitive advantages. Internal data is often generated automatically by the user's interaction with the e–commerce data (e.g. clickstream–data), but may also be rendered manually (e.g. broad recommendation lists based on editors' manual selections).

3.2 Output Data of Recommender Systems

The outputs of recommender systems are suggestions of items (i.e. products and services). Additionally, the may display ratings, text comments, predictions and explanations.

Suggestions make the user of recommendations systems aware of items that the e–vendor considers as useful to the customer. Phrases like "we recommend...", "try this". Other phrases ("additional products", "supreme products") are used to indicate the cross– and up–sell potential of certain items. Recommender systems may suggest either only one item or may display multiple items to the user. When a set of items is recommended by lists, the order of items may be arbitrary, which means that the sequence of items does not reflect any order of preference for the user (e.g. alphabetical). In the other case, the order of items may indicate predictions of the degree of interest to the user (i.e. the first item on the list is the best–fit recommendation).

Predictions are estimates of ratings, the user would give to items. They quantify, how much a user will probably like the recommended item and hence indicate the strength of an recommendation. Predictions may be personalized, which means that they are based on the stored preferences in an individual user–profile. Non–personalized predictions refer to estimates for typical community members [SKR01].

Text comments and ratings constitute further possible output data of recommender systems. Suggestions of items may be supplemented by text comments. Because text comments are not completely machine–understandable, many e–vendors require the user to give an additional numerical rating to indicate the direction of the comment (i.e. pro or against the item). Especially, when the size of the community is large and the number of text reviews is high, the recommender system has to display a selection of text comments, because showing all text comments would lead to information overload. The selection of text comments bears the risk of biasing information (e.g. only positive comments are shown to the user). Hence, accompanying numerical ratings can be used to show an representative selection of comments to the user by choosing a proportional number of positive, neutral and negative comments. Another notion to address the problem of selecting text comments is to apply "meta–ratings". Meta–ratings are ratings about ratings (respectively text comments). This means, that the usefulness and quality of text comments from the community are judged by the community (e.g. "Was this review helpful to you?"). In this case, the most appreciated text comments are displayed first.

In recommender systems *explanations* can be used to expose the reasoning behind an recommendation. They enhance transparency in the recommendation process. Thus, they may raise the user's trust in the recommendation process and may also improve the decision–making performance. The benefits of adding explanation capabilities to recommender systems are [Her99]:

- Justification: The users gets an understanding of the reasoning behind the recommendation. This alleviates the decision of how much confidence to place in a recommendation.
- User involvement: User involvement is improved, because explanations allow the user to add his knowledge and inference skills more easily to the recommendation.
- Education: The user will better understand, how recommendations are generated as well as strengths and limitations of the system.
- Acceptance: Explanations raise the acceptance of the system as a decision aide, because strengths and limitations are better understood and suggestions are justified.

Since recommendation methods range from relative simple to highly complex with large amounts of data and extensive computation (see Section 3.5), the provision of explanations may also vary in terms of complexity. Three possible models for explanations are applicable [Her99]:

- Data–explorative model: When this model is applied, the application lets the user explore the data on which recommendations are based. Mathematical processes behind the recommendations are not explained (e.g. because they are to complex for the "average" user). Because some recommendation methods use large amounts of data, initially only a selection of key–data are displayed to the user. Key–data are of significant relevance for the recommendation process. However, the user can navigate to other parts of the data. The data–explorative model allows the user to validate the recommendation by their own personal approaches. For instance amazon.com applies this model. The user may click on a link labeled "Why was I recommended this?" to see the relevant items for the recommendation process as shown in figure 3.2.

Figure 3.2: Explanations using the data–explorative model

- Process–explorative model: In this case, the recommender system tries to explain the mathematical process on a high level. For example flowcharts may be used to visualize the process–steps of recommendation process. The user may take a closer look at the individual steps and change the computation by altering parameters.

- Argumentative model: In this model, the explanation facility of the recommender systems works as an agent that uses logical argument techniques to support a conclusion. The system makes claims at multiple stages. The user can challenge the inference and data of each claim. In this model the amount of data processed by the user is minimized.

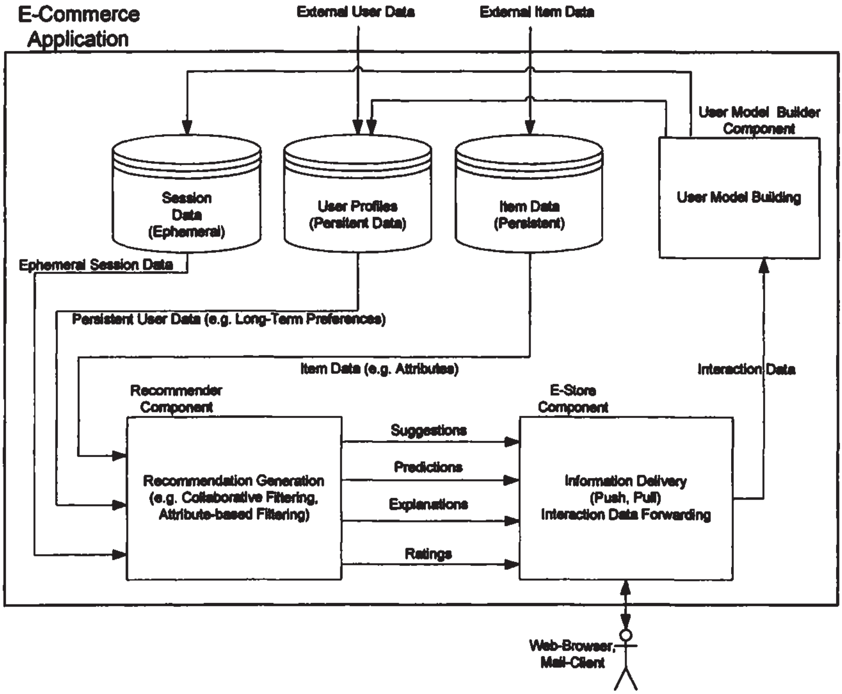


Figure 3.3: Flow of input and output data

Figure 3.3 summarizes *the basic flow of input and output data* in e–commerce recommendation applications and denotes the software components of a typical recommender system.

As illustrated in the figure, an e–store component is in charge of the information delivery to the user by applying push or pull technologies. The component also forwards the interaction data to the user model builder, which constructs a long–term and/or short–term user profile and stores the user profile(s) in a database.

The user profile stored in the database is employed by the recommender component. This component generates the suggestions, predictions, and explanations and summarizes ratings by applying recommendation methods (e.g. collaborative filtering, attribute–based filtering). This process is typically based on session data, the long–term user profiles and item data. Additionally external data regarding users and items (i.e. data that stems from third party sources) may be used in this process.

3.3 Measurement Scales for Preference Elicitation

Preferences of users are the most important data for recommendation systems. They are generally used as input data but – as mentioned in Section 3.2 – may also be displayed as an output in form of predictions. To measure or indicate these preferences, different *statistical measurement scales* can be applied. Measurement scales can be categorized into *nonmetric (qualitative)* and *metric (quantitative)* scales [HATB98, BEPW03].

Nonmetric scales include nominal scales, binary scales and ordinal scales. *Nominal scales* are classifications of qualitative attributes, characteristics or properties (e.g gender, color). *Binary scales* are a sub–type of nominal scales with exact two possible occurrences of an attribute (e.g. yes or no, male or female, zero or one). Nominal and binary scales are the scales with the lowest level of measurement precision. Arithmetical operations can not be applied to nominal and binary scales, but it is possible to calculate the absolute and relative frequency of an attribute. With *ordinal scales* variables can be ordered or ranked, i.e. attributes can be compared by "greater than" or "less than" relationships. The ranking of variables is relative. However, it is not possible to determine the distance between two occurrences of a variable. Similar to nominal scales it is not possible to use any arithmetic operation. However, additional to absolute and relative frequency, quantile and median can be calculated.

Interval scales and ratio scales are both metric scales, which refer to quantitative measurable attributes (e.g. amount of time, size of an object, temperature). Metric scales have constant units of measurement, i.e. the distances between two adjacent points are equal on any part of the scale [HATB98]. *Interval scales* have arbitrary zero points (e.g. temperature in Fahrenheit or

Celsius). Possible arithmetical operations for transformations of the scale are addition or subtraction. Feasible statistical operations are (amongst others) to calculate the mean value and standard deviation. Interval scales are widely used for measuring preferences explicitly (e.g. "rate this item on a scale from one to five"). These scores and ratings are regularly assumed to be based on interval scales. However, strictly speaking, ratings rest upon ordinal scales, because it can not be assumed, that equal distances between two adjacent points on the scale are given on any part of the scale. In spite of this, ratings are predominantly treated as interval scales (e.g. building the mean value of all user ratings) [BEPW03]. In contrast to interval scales, *ratio scales* have an absolute zero point (e.g. weight, length, speed). They represent the highest form of measurement precision and all arithmetical operations are allowed. In the context of recommender systems, ratio scales are preferably used when preferences are surveyed by means of implicit data acquisition methods (e.g. time spend viewing an item).

3.4 Information Delivery

The output of recommender systems (i.e. suggestions, ratings, text comments and predictions) may be transferred to the user by push, pull and passive *information delivery techniques.*

Push technologies refer to methods, where the suggestions are given to the user without requiring the users' initiative, i.e. the recommender systems initiates the communication process [MGL97]. A distinctive example for push communication is the use of e–mails to send recommendations to users on a regular basis (e.g. fixed time schedule). This has the advantage of giving recommendations to users without requiring them to interact with the e–commerce application. They can be understood as an promotional activity to invite users to return to the e–commerce vendor. However, if the user is not satisfied with the recommendations (e.g. due to lack of personalization) he or she might consider the e–mails mentioned in the example above as spam.

Passive technologies denote information delivery, which supplements the presentation of recommendations to the normal use (i.e. "the natural context") of the e–commerce application [SKR01]. Hence, the might be understood as a sub–class of push technologies. For instance, recommendations are displayed based on the item the user is currently browsing. Another example for passive delivery is the presentation of supplemental goods or special shipping options during the ordering process. At this time the user may be very receptive to the vendors idea of up– and cross–selling. A possible disadvantage of passive recommendations is that the user might not recognize them as recommendations [SKR01].

In contrast *pull technologies* require the user to take initiative to get recommendations. In e–commerce applications these is usually achieved by clicking on a link (e.g. "your recommendations"). Pull technologies are usually perceived as unobtrusive, because no recommendations are displayed unless the user wants them to see.

3.5 Recommendation Methods

This Section focuses on specific recommendation methods. Recommendation methods can be classified according to the degree of personalization. Methods for non–personalized recommendations do not refer to individual user profiles. Thus they give identical recommendations to different users. Methods for personalized recommendation refer to individual user profiles, which may be based on persistent or ephemeral data. Consequently they offer recommendations adapted to the individual user.

Figure 3.4 gives an overview of varying degrees of personalization of recommendations regarding (1) the target of recommendations, (2) the typical recommendation method(s) applied, (3) the characteristical data acquirement method, and (4) the deployment of user–profiles.

General recommendations are suggestions that are given to all users of a recommender system. Typical recommendation methods are statistical summarization (e.g. Top sellers of all customers of an e–commerce application) and manual selection. Usually no user–specific information is necessary to give this kind of recommendations. As a consequence a user profile is not deployed.

Degree of Personalization

Type of Recommendation	Target	Typical Recommendation Method	Typical Data Acquirement	Application of User-Profiles
Personalized Recommendation (Persistent, Long-Term Perspective)	Individual User	Information Filtering	Explicit and Implicit	Yes (persistent)
Personalized Recommendation (Ephemeral, Short-Term Perspective)	Individual User	Association Rules based on Items in Shopping Basket	Implicit	Yes (ephemeral)
Group-Specific Recommendation	Group of User	Statistical Summarization	Explicit	Yes (persistent)
General Recommendation	All Users	Manual Selection (e.g. Editors' Picks) Statistical Summarization (e.g. Top-Sellers)	None	No

Figure 3.4: Degrees of personalization

Group–specific recommendations are tailored towards a group of users. Usually statistical summarization is applied to generate recommendations for each group. Data acquirement usually takes place by explicit user interrogation (e.g. by offering fields of interest the user can specify, asking for demographic data). If the number of groups the users are segmented into is small, manual selection is also a possible alternative. *Personalized recommendations with a short–term perspective* are suggestions adapted to the individual user. However, a persistent personalization approach is not pursued. This is suitable, if a authentication of the user is not possible or desired. In e–commerce applications short–term personalized recommendations are often based on items in the virtual shopping basket. Based on this items, complementary items may be recommended to increase cross–sales. Product association rules may be used for this purpose. Ephemeral personalization regularly uses user–profiles to store user–related information. Albeit the profile may be discarded after the user quits the interaction session. *Personalized recommendations with a long–term perspective* are also adapted to the individual. Information filtering methods in conjunction with persistent user–profiles are typically used to achieve long–term personalization.

Figure 3.5 shows a categorization of recommendation methods based on the personalization criterion. Personalized and non–personalized recommendation methods as well as their advantages and disadvantages are discussed in detail in the following sections.

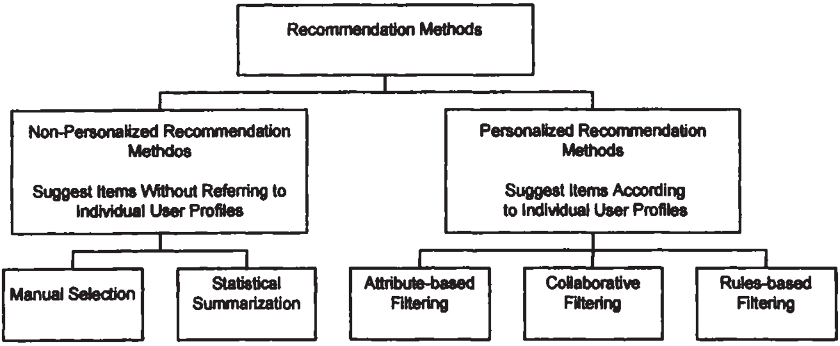


Figure 3.5: Classification of recommendation methods

3.5.1 Non–Personalized Recommendation Methods

Non–personalized methods do not adapt recommendations to the user. Hence, all users get identical recommendations. Non–personalized recommendation methods generally require little (statistical summarization) or no (manual selection) computational power. In regard to privacy these methods are less problematic, because mapping tastes, preferences, individual characteristics etc. to individual users is not necessary for the recommendation process.

Manual selection refers to the creation of lists of items to recommend by editors, critics, artists and other experts. These lists reflect the personal interests, tastes, preferences and objectives of these specialists and are made available to the community. These lists are regularly supplemented by text comments for the individual items to get a better understanding of the recommendations. This method does not require any machine computation at all. Manual selection is a traditional form of providing recommendations and has been used by magazines, newspapers etc. for a long time. By nature, manual recommendations are prone to bias, because they rely on a single persons preferences [SKR01]. However, because they are based on the opinion of experts they may offer deep insights to the items, especially when recommendations are accompanied by high quality text comments. Some e–stores encourage "normal" customers and community members respectively to create manual recommendation lists (e.g. "Listmania Lists" at Amazon.com). Links to specific customer generated lists may be displayed while browsing the product catalogue, if the current article is a part of these lists.

Statistical summarization denotes the aggregation of community opinions and community popularity. Typical examples of these summarizations are the number of community members, who like or purchase an item or the arithmetic mean of community ratings. A more complex method is to use *association rules* for recommendation purposes. Association rules may be applied on the shopping basket data (i.e. items purchased on a per–transaction basis) of e–stores [AIS93, SVA97]. A typical example for an association rules would be the finding, that 80 per cent of people, who bought the book "The Last Juror" by John Grisham also bought the "The Da Vinci Code" by Dan Brown. Association rules consist of three elements: (1) the antecedent (in this example "The Last Juror") (2) the consequent ("The Da Vinci Code") and (3) the confidence factor ("80 per cent"), which expresses the strength of the rule.

Table 3.1 shows a simple example of a customer–item matrix for basket data. The columns include different items, the rows contain the customers. A check-mark indicates, that a certain customer has bought the item.

Table 3.1: Basket data: example of a customer–item matrix

	Item A	Item B	Item C	Item D	Item E
Customer A	✓				✓
Customer B	✓		✓		✓
Customer C		✓			
Customer D				✓	✓
Customer E	✓		✓		

The customer–item matrix is transformed into an item–item matrix as shown in Table 3.2 by summing up the individual purchase entries. The result of this transformation is always a symmetric matrix (i.e. entries are symmetric with respect to the main diagonal). In this case the figures in the cells show the absolute number of customers who bought a particular item. For example if a customer browses item E, item A (matrix value: 2) would be recommended in the first place followed by item C (value: 1) and D (value: 1).

Product association rules are generally non–personalized (e.g. every customer,

Table 3.2: Basket data: example of a item–item matrix

		also bought...				
		Item A	Item B	Item C	Item D	Item E
Customers who bought...	Item A			2		2
	Item B					
	Item C	2				1
	Item D					1
	Item E	2		1	1	

who browses item E will be recommended item A) but can simply be extended to a low level of personalization by using ephemeral navigation patterns (click–streams). In this case the values in the corresponding lines may be aggregated. For example if a customer has viewed item A and is currently browsing to item E he or she will be displayed item C (aggregated value: 3) as a recommendation in the first place. Additionally item D (aggregated value: 1) may be recommended. More complex personalized recommendation methods are explained in the following Section.

3.5.2 Personalized Recommendation Methods

This Section deals with methods for generating personalized recommendations. Personalized recommendations are adapted to the individual users on the basis of knowledge about their preferences and behavior [AT05]. In the following sections the personalization process is illustrated. A general synopsis of information filtering methods is given, characteristics of information filtering methods are described and information filtering is compared to information retrieval. Finally, collaborative filtering, attribute–based filtering, and rules–based filtering are discussed in detail.

Providing personalized recommendations constitutes an iterative process that is shown in Figure 3.6 and includes the following four stages [AT05]:

1. Define goals and evaluate appropriate personalization approaches: Personalization initiatives should be tied to discrete and quantifiable business goals (e.g. increase cross–sales by 10 per cent). Depending on this

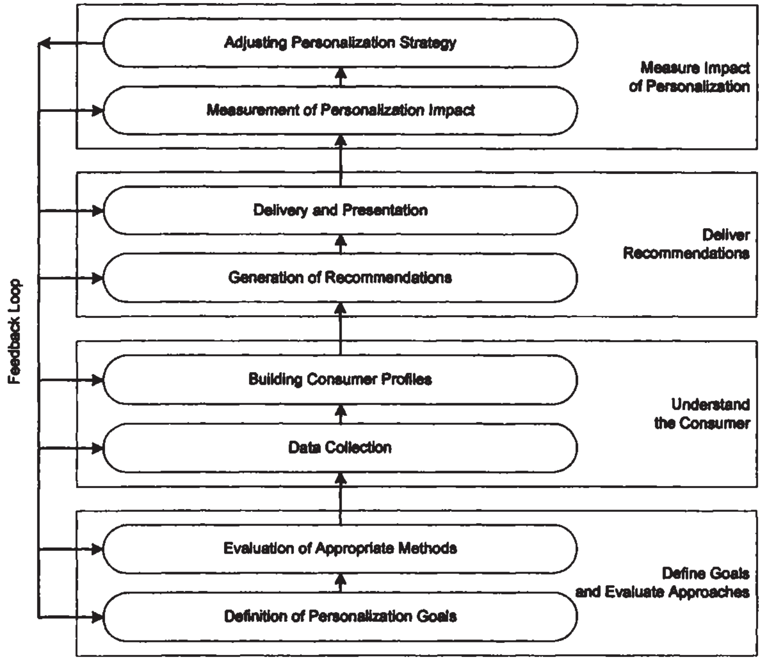


Figure 3.6: The personalization process (adapted from [AT05]).

goals and the general condition (e.g. customer base, characteristics of the offered products and services) appropriate personalization approaches have to be evaluated. The pros and cons of the specific approaches (i.e. information filtering methods) are described below.

2. Understand the consumer: This is achieved by collecting comprehensive information about consumers and converting it into knowledge that may be used for personalized recommendation purposes. This information is stored in the user profiles.

3. Deliver personalized recommendations: Based on the data collected in Step 2 the most relevant products and services have to be delivered to the consumer by applying appropriate information filtering methods. As discussed in Section 3.4 push, pull, and passive delivery may be chosen.

4. Measure impact of personalization: The last step includes the measurement of the impact of personalization and adequate responses by adjusting the personalization strategy. Measuring personalization impact serves as a feedback for possible improvements of the whole process. This feedback may help to decide whether to collect additional data, build better user profiles, develop better recommendation algorithms or improve the information delivery and presentation [AT05].

3.5.2.1 Synopsis of Information Filtering Methods

Recommender systems apply information filtering methods to deliver personalized recommendations. Information filtering systems share the following characteristics [BC92]:

- Information filtering systems are designed for unstructured and semi–structured data instead of structured data. Structured data conform to a certain format and are "well–defined". Well–defined denotes that the meaning of data is defined unambiguously in an mathematical or logical way through axioms. A typical example for structured data would be a record set in a relational database with simple data types. Unstructured and semi–structured refer to data which have high complexity but no or much less well-defined meaning. A typical example for semi–structured data would be an e–mail, which has structured and well-defined header fields but an unstructured body.
- Information filtering is primarily applied on large amounts of textual information, but may also deal with other unstructured data like images, audio and video.
- Filtering is based on individual or group profiles. Profiles ideally represent the long-term interests and preferences of the individual or group.
- Information filtering may either remove irrelevant information (i.e. "leave things out") or may select relevant data (i.e."selecting things from a larger set of possibilities" from an incoming stream of data [MGT+87]. In the first case the user is presented the data, which is left after the

filtering process (e.g. junk mail filter). In the latter the user sees only the extracted data (e.g. "your recommendations" at amazon.com).

However, these characteristics are not exclusive to information filtering systems and are also valid for information retrieval systems, which makes it necessary to further distinguish information filtering from information retrieval along the following aspects [BC92, HSS01]:

- Frequency of use: Information filtering systems are designed for a repeated and continuous application by the user, who has long–term goals or interests. In contrast information retrieval systems are primarily characterized by an ad–hoc use of an one–time user with an one–time information need.

- Representation of information needs: In information filtering systems the users' needs in respect of information are represented by user profiles. Information retrieval systems apply queries instead of user–profiles as a representation for the information needs.

- Dynamics of data source: Information filtering is predominantly used on dynamic data streams, where irrelevant information is removed or relevant information is selected from that data stream. Information retrieval is applied on relatively static databases, where relevant information is selected.

- Timeliness: For information filtering up–to–dateness of the relevant information is of major importance (which is reflected by the dynamic nature of the data source). In information retrieval, timeliness is not that essential.

- Heterogeneity of users: Information filtering systems deal with undefined, highly heterogeneous user communities in various domains (e.g. entertainment). Information retrieval systems operate predominantly in environments with homogenous and well defined user groups in specific domains (e.g. science and technology).

- Privacy: Because information filtering systems apply user profiles which may contain sensitive personal data, it is highly concerned with privacy issues, which are mostly of no interest to information retrieval systems.

3.5.2.2 Human Approaches towards Information Filtering

Based on organizational studies, Malone et al. identified three basic filtering approaches for persons: cognitive, social and economic filtering [MGT+87]. These concepts of human approaches towards information filtering are incorporated into information filtering systems. The characteristics of these approaches are [MGT+87, HSS01]:

- Cognitive Filtering: Cognitive filtering refers to the attributes, contents and characteristics of an information object. This means that the person, who filters uses the information object characteristics (e.g. content of an e–mail header, title of an book) to judge the relevance. For instance, if a researcher looks for the specific keywords "call for papers" and a title of a conference in received e–mails to get an overview of relevant conferences, he or she employs the cognitive filtering approach. Because cognitive processes are generally attributed to humans, the term cognitive filtering is seldom used in the context of recommender systems. Thus, in literature the terms *"attribute-based filtering"*, *"content–based"* and *"feature–based filtering"* are used to describe techniques, that mimic this filtering approach in information systems.

- Social Filtering: According to this approach a person uses his social network for filtering purposes. It works by supporting the personal and organizational relationships of individuals in a community. If a person considers to give a high-priority to an e–mail, because it is sent from his supervisor, he or she uses social filtering. In recommender systems the idea of *collaborative filtering* is based on a social filtering approach.

- Economic Filtering: By using economic filtering a person employs cost–benefits assessments and explicit or implicit pricing mechanisms on information objects. Cost versus value decisions are taken to decide whether or not to process an information object. If a person decides to read the executive summery instead of the whole report, because his or her workload is high, economic filtering is utilized.

3.5.2.3 Collaborative Filtering

Collaborative filtering is an approach which applies *similarities between users' tastes and preferences* for recommendation purposes. The basic idea behind collaborative filtering approaches is that the active user will be recommended items, which other users liked in the past (user–to–user correlation) [SKR01].

The term collaborative filtering was *first used in literature* by Goldstein et al. [GNOT92]. This paper describes "Tapestry", a document filtering system developed at the Xerox Paolo Alto Research Center, which used collaborative filtering to reduce information overload. Tapestry enabled the user to annotate documents (e.g. e–mails, NetNews articles) with text comments and ratings (explicit approach) but also used implicit feedback (e.g. reply to an e–mail as an indicator for relevance) for recommendation purposes. The tapestry system suffered from two problems. Firstly, a small number of users used the system. Because of the absence of a critical mass of users most of the documents were not annotated and hence could not be used for recommendations. Secondly, Tapestry required the user to describe the filtering needs by a complex SQL-like language. This was a hindrance for users to operate the system [ME95]. Other early implementations of collaborative filtering systems were Grouplens, Ringo and Video Recommender.

In literature, the distinction between *active and passive collaborative filtering systems* can be found [ME95, Run00]. In active systems users actively recommend items to other users (push communication). Active collaborative filtering closely mimics the common practice that people recommend interesting items to other people of their social network (e.g. friends or colleagues). Active collaborative filtering systems support this process by providing information systems as communication tools. Active collaborative filtering requires the user to know interests and preferences of other users. Hence, active systems are of limited scalability. Because of this shortcoming, e–commerce applications regularly apply passive systems for recommendation purposes. In passive systems, the user does not actively recommend items to other users. A direct communication between the users is not necessary. Passive collaborative filtering uses automated information systems in which people provide recommendations as inputs. These inputs are aggregated and directed to appropriate recipients by the system automatically [SV99]. Consequently, passive systems are also referred to as automated collaborative filtering systems.

Table 3.3 illustrates the basic idea of (passive) collaborative filtering based on a simple example. It shows a sample user–item matrix, in which preferences are measured on a binary scale. A "+" indicates that a user liked the item. A "-" means that the user does not like the item. An empty cell indicates, that the user has not rated the item (missing value).

Table 3.3: Collaborative filtering: example of a user–item matrix

	Item A	Item B	Item C	Item D	Item E
User A	+	+		-	+
User B	+		+	-	+
User C	-	+		+	
User D	-			+	+
User E	+		+	-	

Let's assume recommendations are given tho user E. User E is very similar to user B, because both liked item A and item C and disliked item D. Because user B also liked item E, item E will be recommended to user E in the first place. User A is less close to user E (both liked item A, and disliked item D). Hence, item B could be recommended to customer E additionally. Between user E, user C and user D are no similarities at all. Consequently preferences of user C and user D are not used to give recommendations for user E.

Different statistical methods or machine–learning techniques are applied to calculate the similarity between users. *Memory–based techniques* directly compare users against each others (similar to the example above). They operate over the entire user–item matrix using *statistical methods* to perform similarity measures between the users. Correlation–based approaches use the Pearson correlation coefficient ("correlation–based') to determine the similarity between users [RIS+94, SM95, Paz99]. Other memory–based methods use the cosine ("cosine–based") [BHK98, SKKR00] to calculate the proximity between users. In contrast *model-based approaches* use the users' historical rating data to derive a model. This model is used to make predictions, how the individual users will like certain items. Various *machine-learning techniques* – including Bayesian networks [BHK98], neural networks and latent semantic indexing [FD92] – are used to generate recommendations [Bur02]. However, the latter two techniques typically do not rely on user-ratings solely. Additionally they include attributes of the items (i.e. text documents) in the recommendation process. Hence, they can not be regarded as "pure collaborative filtering systems".

The typical *application domain* of recommender systems based on collaborative filtering is to suggest items, whose central characteristics and qualities can not properly measured with "objective" criteria (e.g. books, movies, music) [Run00]. Hence, this items are highly subject to personal taste and preferences.

In order to give reasonable recommendations, correlations of preferences have to exist between users and items. This means that certain groups of users with similar preferences for certain groups of items are given. Collaborative filtering requires a *sufficient number of users* ("critical mass") and an adequate number of known preferences (i.e. ratings of items) stored in user-profiles to give reasonable recommendations. Because collaborative filtering is based on ratings of a community, it employs human judgement. Thus, it enables the exchange of human knowledge between a large number of people without the requirement of knowing each other personally. This makes collaborative filtering a very powerful approach for recommendations.

In contrast to attribute-based filtering (see Section 3.5.2.4) collaborative filtering systems can give recommendations for items, which have no *"objective" commonalities* in terms of attributes with items the user liked in the past. This may lead to very innovative recommendations from the users' perspective. In fact, the recommendations are founded on relationships between the users of the recommender system, hence similarities between item characteristics are not necessary. For instance, a collaborative filtering systems may recommend a book to the active user because of his past ratings of music or movies. This would be hard to achieve with attribute-based or rules-based systems, because music and books generally have different attributes (an exception would be if a songwriter also works as an book–author; in this case an attribute–based system could recommend books written by the songwriter, because they share the attribute "author").

Collaborative filtering approaches are subject to some *limitations* [BS97, Run00, SKKR00]. The *new user problem* refers to the challenge of giving accurate recommendations to new users. Because the preferences of new users are unknown it is impossible to make appropriate recommendations. An approach to address this problem is to use non–personalized recommendation methods (e.g. manual selection and association rules) until sufficient preferences are gathered from the user.

The *new item problem* reflects the hindrance to make recommendations for items, which have not been rated by the community. This is usually the case, when new items are added to the database. Because pure collaborative filtering systems solely use community ratings instead of item attributes for the recommendation process, new items can not be recommended [AT03]. Possible solutions are to use non–personalized methods or to combine collaborative filtering with attribute–based filtering ("hybrid approaches") [Bur02, SPUP02]. However the later requires that the object can be reasonably described by objective criteria. These approaches may be accompanied by incentive programs to get ratings for new items (e.g. to offer vouchers for users who write text comments and add ratings to items, which have not been previously rated).

Rating sparsity means that the number of given ratings is usually very small compared to the number of items, which may be recommended. This may occur, when the number of users is too small (absence of critical mass of users), when the underlying database of items is rapidly changing or when the users are "too similar" (i.e. all users like and rate the same small set of items). These phenomena lead to a high number of "missing values" [Run00] in the user–item matrix and consequently reduce the quantity ("reduced coverage" because products with no ratings can not be recommended) and quality of recommendations. To address this problem hybrid–approaches may be used. For instance, if the user–profile includes demographic data (e.g. gender, age, education), this information may be used to find similar users not solely based on similar ratings of items but also on demographic compliance ("demographic filtering") [Paz99].

The *unusual user* refers to a user, whose tastes are very different from the rest of the population. Hence, it is impossible to find any "nearest neighbors" (i.e. like–minded users) to derive recommendations from their ratings. Hence, the quality of recommendations for this kind of user are poor.

Collaborative filtering systems perform complex mathematical operations over large amounts of data. For the user it is hard to understand, why a certain item is recommended. This is called the *"Black–Box problem"*. A possibility to enhance transparency of the recommendation process is to display explanations (see Section 3.2).

Scalability problems may arise when collaborative filtering methods are used, because with this technique computation grows with the number of users and the number of items. In e–commerce applications these systems are challenged with millions of users and items. Consequently serious scalability problems may occur [SKKR00]. This is especially the case when memory–based algorithms are used. As mentioned above, memory–based algorithms operate over the entire database (which contains the user–item matrix) to give recommendations [BHK98]. Hence, this algorithms are prone to scalability problems. In contrast model–based approaches use the database to estimate parameters of a model in advance. This model is used to give recommendations to individual users after the calculation of the model parameters. Thus, it is not necessary to access the whole database while giving recommendations to the user. Consequently, model–based approaches outperform memory–based algorithms but may show a lack of accuracy, especially when the database is frequently changing [BHK98].

Collaborative filtering systems *disregard product attributes* for recommendation purposes, even when they are of high relevance. Pure collaborative filtering systems are not reasonably applicable, when the "objective" criteria of the recommended items are dominating the user's preferences. For instance in the application domain of personal computers, objective attributes (e.g. performance data) have a strong influence on the buyers decision making process. The impact of subjective criteria (like the user's brand affinity) on the buying decision may still be given, but is usually of less importance. Consequently, the quality of recommendations based on collaborative filtering techniques may be considered as poor, because the user's requirements regarding these objective attributes are not taken into consideration. In addition, associations of items based on similarities between item characteristics can not be discovered by collaborative filtering systems. For example, a user likes films directed by Robert Rodriguez. A collaborative approach can not recommend all movies, music or books by Robert Rodriguez, because the attributes (e.g. "directed by", "composed by" and "written by") and the corresponding relationships are not modelled in pure collaborative filtering systems.

3.5.2.4 Attribute–Based Filtering

Attribute-based filtering is an filtering technique, which uses similarities between items for recommendations. This fundamental assumption is, that a user will like items similar to the ones he or she liked in the past [BS97].

In attribute–based filtering systems, the interest of a user is determined by the associated features of items. Hence the term *"feature-based"* approaches is also used for such systems [Run00]. Because the basic idea of this method is an outgrowth of information filtering research and was initially applied on textual documents, the term *"content-based filtering"* is a further term found in literature to describe such systems [BS97, Bur02, HSS01]. Strictly speaking, content–based approaches are a subclass of attribute–based filtering systems, where the application domain is textual documents. These documents are described by a restricted number of attributes of the content (e.g. characteristic words) [SPK00].

Similar to collaborative filtering, attribute–based filtering approaches employ a long–term user–model to learn and store user–preferences. In contrast to collaborative filtering, the interests of the user are not determined by comparing the similarity of the user to other users. Instead the interests of the user are derived from the attributes of the items, the user has already rated. Hence, attribute–based filtering systems generate recommendations based on a user–profile built up by analyzing the attributes of items which the user has rated in the past [BS97].

When designing a content–based filtering system two problems have to be addressed [Paz99]:

1. The representation of the items to recommend: This refers to the selection of relevant characteristics of the items to recommend. Depending on the application domain, this could be a fairly straightforward or rather complex task. For instance, when applied to automobiles the representation might focus on key–characteristics (i.e. specifications like horse–power, transmission, fuel economy etc.). In other domains (recommendation of textual documents, i.e. "content–based filtering") finding the right representation of items is more complex. For instance, the hybrid–recommender system Fab [BS97] uses the 100 most "important" words to represent documents, which are recommended to the users. The determination of the importance is determined by a weighting measure. For instance Fab uses the term "frequency/inverse document frequency measure" (TF–IDF) [Sal89] to gather the most informative keywords of web–pages.
2. The employment of a classification algorithm on user–profiles: A classification algorithm is used to estimate the degree of interest in the item. The user–profile contains ratings based on the classification scheme developed in Step 1. These ratings may be surveyed explicitly or implicitly. In literature a variety of classifications algorithms are used based on different statistical or machine learning methods (e.g. cosine similarity measures, Bayesian classifiers, clustering, decision trees, and artificial networks) [PB97].

Table 3.4 illustrates a representation scheme as described above in conjunction with a user profile. In this simple and fictional example books on e–commerce are represented by four keywords. A checkmark indicates that the term corresponding term occurs in the description of the book. A "+" in the column of "User A" means, that the user was interested in the book. A "-" indicates, that the user was not interested in the book. Because Book E and F are unknown to the user, they can be used for recommendation purposes. For example Book E might not be of interest, because in the past the user was not interested in books, which dealt with E–Branding. However, he or she might be interested in "Book F", because it covers topics the user is interested in.

Applying attribute–based filtering requires two preconditions: (1) The items can be described by "objective" criteria and (2) there must be a significant

Table 3.4: Attribute–based filtering

	Last Mile Logistics	E–Branding	E–CRM	Business Models	User A
Book A		✓	✓		-
Book B	✓			✓	+
Book C	✓	✓		✓	-
Book D	✓			✓	+
Book E		✓			?
Book F	✓			✓	?

coherence between these criteria and the global preferences of the users of attribute–based recommender systems [Run00].

Consequently, attribute–based filtering systems are well suited for domains where subjective tastes are not dominating the selection process and judgments are merely based on "hard–facts" (e.g. technical products). A typical example are digital cameras, which can be described with technical data. However, subjective criteria (e.g. design, brand–attitude) might still play a considerable role in the purchase decision process. Attribute–based filtering systems have limitations in the incorporation of these subjective criteria.

In contrast to collaborative filtering, attribute–based filtering methods do not depend on ratings of other users than the active user. Hence, attribute–based filtering systems are faster applicable than collaborative filtering systems, because building a "critical mass" of users is not crucial for the deployment of attribute–based systems [Run00].

A further advantage of is the structured representation of the attributes of items. Consequently, these meta–data could be used for purposes that go beyond attribute–based filtering. For example, the search for specific attributes is easy to implement (e.g. "show all books written by Umberto Eco"). Rules–based filtering approaches (see Section 3.5.2.5) can further be applied, when structured meta–data of items are already existent.

However, attribute–based systems are prone to some limitations. *Limited content analysis* refers to the fact, that attribute–based systems are limited by the attributes that are explicitly linked to the items these systems recommend [AT03]. Depending on the domain, these features can be extracted automatically or have to be assigned by hand. As mentioned above, information retrieval offers a variety of methods to extract features of textual documents automatically. However, in other domains (e.g. multimedia–data) automatic feature extraction is much more complicated [BS97]. The assignment of attributes by hand is a time consuming task, which is often not practical due to limitations of resources [SM95]. Depending on the application domain a further problem with limited content analysis may be that two items with the same associated attributes may be indistinguishable. This may be of no concern when the two items are equivalent (e.g. technical products with the same specifications). However, if attribute–based filtering systems are applied on textual documents ("content–based filtering") a problem might occur. Textual documents are usually represented by the "most important keywords". Consequently, a well–written article can not be distinguished from a bad one, if the same terms are used [SM95].

Over–specialization is a further shortcoming of attribute–based systems. Because this kind of filtering system can only recommend items that score highly against the active user's profile, the user is limited to get recommendations of items that are similar to those already rated [BS97]. Consequently, the recommendations of attribute–based systems may not appear as "innovative" to the user compared to recommendations based on collaborative–filtering algorithms. In some fields of application, items that are to similar should not be recommended (e.g. articles in different newspapers, which describe the same event). Hence in some cases it may be sound to filter out items which are too similar to the ones the user has rated or seen before additionally [AT03].

Similar to collaborative filtering, attribute–based filtering systems also face the *new user problem.* If the number of ratings in the user–profile is insufficient, the system is not able to give accurate and reliable recommendations.

3.5.2.5 Rules–Based Filtering

Rules–based filtering is an approach that employs *business–rules* for recommendations. In this context, rules describe on–line behavioral activities of the users [AT01]. In general, rules–based approaches can be designed stereotypical or personalized [KSS03]. In stereotype rule–based filtering approaches, the individual user is assigned to a group of similar users. For filtering purposes, the identical set of rules is used on each member of the group. In contrast personalized rules–based filtering systems apply an individual set of rules for each user [KSS03]. Consequently, the degree of personalization is higher with the latter approach.

Rules–based approaches are widely used in the field of expert systems for knowledge representation purposes [Jac98]. Generally rules may be described in the following form: IF {predicate} THEN {result}. In personalized rule–based filtering approaches a user profile contains a *set of rules*, that expresses the preferences of an individual user [KSS03]. For instance: IF {book_abstract contains "Macroeconomics" and book_year_of_publication not less than 1995} then {user_relevancy = "very high"}.

The main task of rule–based approaches is to *discover suitable rules*. In general, finding appropriate rules is accomplished with human experts (e.g. a marketing manager). Consequently, the effort for employing rules–based approaches tends to be higher compared to collaborative and attribute–based filtering methods due to the involvement of *human expertise*.

Figure 3.7 shows a *structured approach* towards the rule discovery process. In order to get "truly" personalized recommendations, rule discovery methods are applied to the data of every single user. The process of discovering rules could be divided in two phases: (1) data mining and (2) validation of the rules [AT01].

In the first step, *data mining methods* are applied on the user data to generate a large set of rules. Many of these rules are trivial, spurious and not relevant in the given application domain [AT01]. Hence step two, i.e. *rule validation*, is an important issue with this approach to get high–quality recommendations. Because of the sheer number of rules and users in e–commerce applications it is impossible to validate each rule for an individual customer by a domain expert. Consequently, rule validation is not performed separately for each user, but for all users at once by applying rule validation operators. Because there are many similar or identical rules across different users, validation effort can

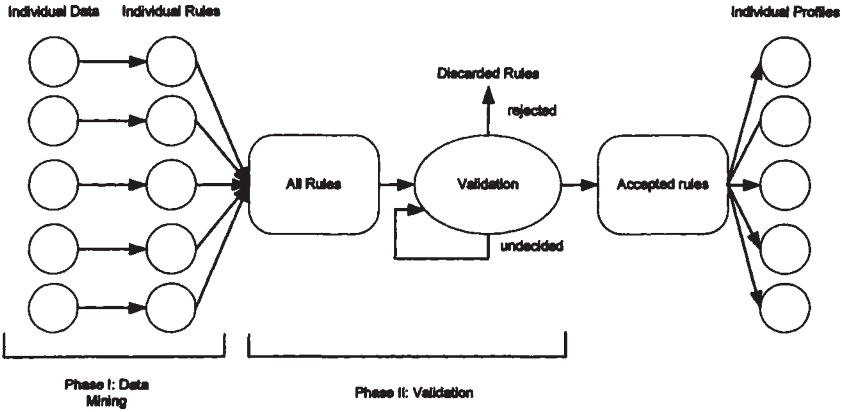


Figure 3.7: The rule discovery process [AT01]

be significantly reduced. In the end, the accepted rules form the profile of the individual users. For a detailed description of this process see [AT01].

One of the major drawbacks of rules–based filtering is the relative *static* nature of this approach. In contrast to collaborative filtering, changes in the taste of the user–population is reflected over the time due to the permanent rating of items by the users. However, in rules–based approaches the rules stay the same until a new discover and validation process is initiated. Because this process uses human expert knowledge, the effort of updating the rules is much higher compared to the "automatic" collaborative–filtering approach.

Chapter 4

Research Model, Hypotheses, and Methodology

This chapter deals with the research model. In the first step the problem statement of the work is defined. Based on that, the research questions and the research model are elaborated. Thereafter, the hypotheses are summarized. The chapter ends with a section that deals with methodological aspects.

4.1 Problem Statement

The majority of research literature regarding recommender systems deals with this topic from the viewpoint of computer science. The focus is on the underlying algorithms for generating recommendations [KSS03, SKKR00, BS97, Bur02, SVA97, Run00]. The existing research concerning the marketing perspective (e.g. the influence of recommendations on consumers decisions) is still scarce [SN04, HK04, HM03, CLA$^+$03, HT00].

The book strives to identify the underlying psychographic factors of consumers that determine: (1) the interest in *personalized recommendations*, (2) the interest in engaging actively in virtual communities of transaction located at online purchase environments by *submitting product–related ratings and comments*, and (3) the interest in *product-related opinions of other consumers* in virtual communities.

Virtual communities are important for recommendation applications, especially if collaborative filtering is applied for recommending products and services. As mentioned in Section 3.5.2.3, collaborative filtering is an approach which applies *similarities between users' tastes and preferences* for recommendation purposes. The basic idea behind collaborative filtering approaches is that items are recommended to the active user, which other users liked in the past (user-to-user correlation) [SKR01]. Especially when using explicit data acquirement, it is important to have a lively community organized at the online purchase environment in order to learn preferences of consumers for recommendation purposes.

However, when collaborative filtering is applied, the following problems arise (for a detailed description see Section 3.5.2.3):

- A critical mass of community members is required.
- If explicit methods of data acquirement are employed, the members must be willing to submit product-related ratings.
- The members of the community must generally have a positive attitude towards the opinions of other members, because recommendations are based on them.

Consequently it is of interest, which psychographic factors of consumers are tangent to the problem areas mentioned above. The following section deals with the research questions based on these problem areas.

4.2 Research Questions and Model

The central research question of the book is: *Which psychographic factors are of major importance for the acceptance of online product recommendations* *and the commitment to participate in the virtual community of an e–vendor by submitting ratings and comments of products?*

The author tries to address this question by applying the *opinion leadership theory* in the context of online book recommendations. The author has chosen books as the product class because of the following reasons:

- Books are the most prominent product category sold over the Internet worldwide and in Austria [AIM05]. Hence, it is more likely that the respondents of the survey have experience in buying books and with book recommendations respectively.
- Books are a product class where subjective tastes and preferences are of high importance for the buying decision. As a consequence, word–of–mouth and virtual communities are important facets in this product category.
- Selling books over the Internet is a typical application domain for recommender systems based on collaborative filtering or summarization of community opinion.

Opinion leadership is a well–established and well–researched concept in marketing [BME01, MG95]. The term "opinion leadership" was introduced to scientific debate by Lazarsfeld et al. in 1944 [LBG44]. The study of the 1940 presidential election examined the influence of relatives, friends, and coworkers on voting decisions. The concept was applied to the field of consumer decisions by Katz and Latzarsfeld in 1955 [KL55]. Empirical evidence of the importance of opinion leadership was fostered by King and Summers in 1970 [KS70].

In the field of consumer decisions opinion leadership is understood as the *exertion of an unequal amount of influence* by consumers in the purchase behavior of others [FGE96]. In general, opinion leadership stimulates interpersonal communication ("word–of–mouth"). One aspect of this process is that opinion leaders tend to give recommendations to other consumers ("advice giving word–of–mouth"). With the application of recommender systems e–commerce vendors try to mimic or support this process by the use of information systems. Hence, it seems suitable to apply the opinion leadership concept to get a better understanding of online recommendations and community activity in e–commerce environments.

Consequently, the question arises which underlying factors determine opinion leadership. Marketing literature has identified *involvement with the product category* as an important factor of opinion leadership [RRS98, FP87, RD71]. Product involvement is often viewed as the long–term interest in a product class based on the centrality to important values, needs, or the self–concept [Blo81].

Figure 4.1 summarizes the already empirical tested *background theory* of the book. Product involvement positively affects opinion leadership and opinion leadership itself has a positive influence on word–of-mouth [RRS98].

Figure 4.1: Background theory of the book

The research model shown in Figure 4.2 adapts the basic research model *towards e–commerce applications* and includes the *interest in online–product recommendations.* Word–of–mouth is specified as the interest to contribute product–related comments and ratings to the virtual community of an e–vendor. Acceptance of recommendations in general is defined by the interest in receiving personalized online recommendations by an e–commerce application. Further, the opinion seeking concept is added to the model. Opinion seeking occurs, when individuals search out for advice from other consumers when making a purchase decision with respect to a certain product class [FGE96].

Because some inadequacies regarding the involvement variable have been identified in literature [RRS98], the unidimensional approach to product involvement is substituted by the *multifaceted construct of product involvement* proposed by Kapferer and Laurent. According to these authors, involvement is a multifaceted construct along five dimensions [KL86]. It consists of the perceived importance and risk of the product class, the subjective probability of

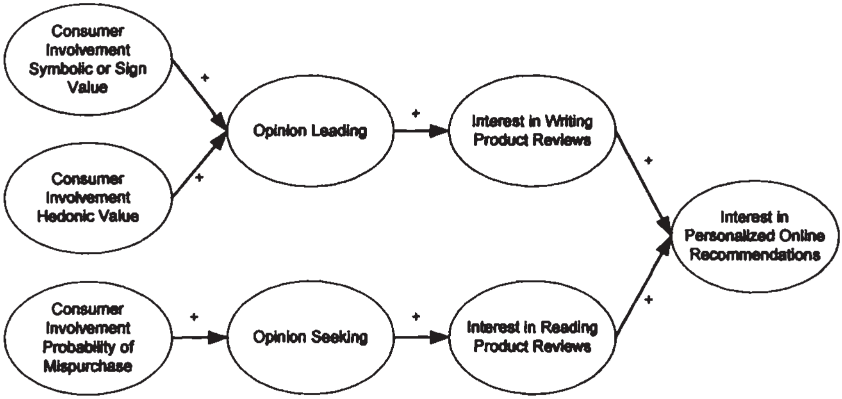


Figure 4.2: Research model

making a mispurchase, the symbolic or sign value, the hedonic value of the product class, the hedonic value of the product class and the interest in the product class.

The author assumes that the symbolic or sign value and the hedonic value facets of product involvement influence the opinion leadership behavior. Furthermore, a positive relationship between the risk of a mispurchase facet and opinion seeking is assumed. Additionally, it is hypothesized that opinion seeking behavior has a positive effect towards the interest in reading product–related comments and ratings. Finally, it is assumed that the participation in a virtual community (i.e. reading and submitting product–related comments and ratings) has a positive influence towards the interest in personalized online recommendations.

Figure 4.3 presents the extended research model, where the influence of further psychographic and sociodemographic factors is examined. Domain–specific innovativeness reflects the tendency to learn about and adopt new products (or innovations) within a specific domain (i.e. product class) [GH91]. It is assumed that *domain–specific innovativeness* has a positive influence on the interest in recommendations. *Impulse buying tendency* is a further psychographic determinant found in the extended model. It refers to the degree to which an individual is likely to make unintended, immediate, and unreflective purchases

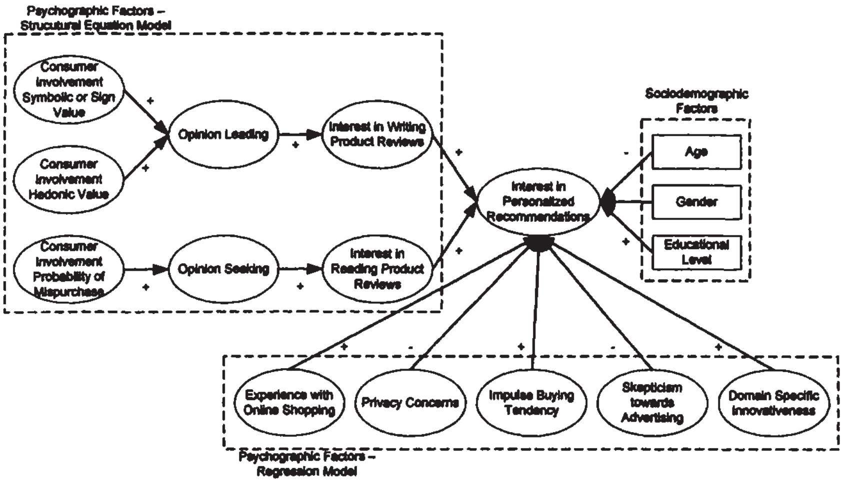


Figure 4.3: Extended research model

(i.e. impulse purchases) [WJB97]. A positive influence towards the interest in personalized online recommendations is expected. A further psychographic factor found in the extended model is *skepticism towards advertising.* This factor is defined as a general tendency toward disbelief of advertising claims [OS98]. Because personalized online recommendations can be understood as personalized kind of advertising, it is assumed that skeptic persons have a lower interest in recommendations. The influence of *privacy concerns* and *experience with online shopping* is also investigated in this extended model.

In addition, the influence of demographic factors (e.g. age, gender, income) are investigated. Table 4.1 summarizes the *hypotheses that are derived from the extended research model* and are investigated in this book.

Besides the influence of psychographic and sociodemographic determinants on the acceptance of recommendations and community activity, the following research questions are addressed in this book by means of exploratory research:

- *Does the delivery of recommendations affect impulse buying behavior?*
- *How important are product-related reviews that originate from different*

Table 4.1: Research hypotheses

Psychographic Hypotheses (Structural Equation Model)

No.	Hypothesis
H1	The higher consumers assess the hedonic value of books, the more likely they tend to engage in opinion leading.
H2	The higher consumers assess the symbolic sign or value of books, the more likely they engage in opinion leading.
H3	The higher consumers assess the risk of making a mispurchase, the more likely they engage in opinion seeking.
H4	The more consumers engage in opinion leading, the more likely they are interested in writing book-related reviews in virtual communities of e-vendors.
H5	The more consumers engage in opinion seeking, the more likely they are interested in reading book-related reviews in virtual communities of e-vendors.
H6	The more consumers are interested in writing book-related reviews, the more they are interested in reading reviews of other consumers.
H7	The more consumers take part in a virtual community, the more they are interested in personalized book recommendations.
H7a	The more consumers are interested in writing book-related reviews, the more they are interested in personalized book recommendations.
H7b	The more consumers are interested in reading book-related reviews, the more they are interested in personalized book recommendations.

Psychographic Hypotheses (Regression Analysis)

No.	Hypothesis
H8	The higher the impulse buying tendency of a person, the higher the interest in personalized book-recommendations.
H9	The higher the privacy concerns of a person, the lower is the interest in personalized book-recommendations.
H10	The higher the online shopping experience of a person, the higher the interest in personalized book-recommendations.
H11	The higher the skepticism towards advertising of a person, the lower is the interest in personalized book-recommendations.
H12	The higher the domain specific innovativeness of a person, the higher is the interest in personalized book-recommendations.

Demographic Hypotheses

No.	Hypothesis
H13	Gender influences the interest in personalized recommendations.
H14	Gender influences the interest in writing book-related reviews.
H15	Gender influences the interest in reading book-related reviews of other consumers.
H16	The older persons are, the lower is their interest in personalized book-recommendations.
H17	The older persons are, the lower is their interest in writing book-related reviews.
H18	The older persons are, the lower is their interest reading book-related reviews of other consumers.
H19	The higher the educational level of persons, the higher is their interest in personalized book-recommendations.
H20	The higher the educational level of persons, the higher is their interest in writing book-related reviews.
H21	The higher the educational level of persons, the higher is their interest in reading book-related reviews.

sources (e.g. other consumers, critics, trusted third parties) for the decision process of the consumers?

- *What are the motives to submit product–related comments and ratings to virtual communities maintained by e–vendors?*
- *What benefits do customers expect from recommendations?*
- *Do the customers object methods of implicit data acquirement due to privacy issues?*
- *Which communication method (e.g. push vs. pull) is preferred for the delivery of recommendations?*
- *How do customers assess the interests and motives of e–commerce vendors regarding online–recommendations?*

4.3 Methodology and Research Design

In the book a *quantitative research approach* is applied. As mentioned above, the research model is tested in the context of book recommendations. Hereby, consumers were asked to answer a standardized web–based questionnaire. The research model shown in Figure 4.2 (see Section 4.2) is verified by the application of *structural equation modeling*. Further, the psychographic determinants shown in Figure 4.3 in the lower box are tested by a *regression analysis*, because including all this factors in a structural equation model would have been overly complex. The demographic factors are verified by a regression analysis and Mann–Whitney tests (for gender–specific differences).

The following multi–item, self–report scales are used for the measurement of the psychographic factors:

- Impulse Buying Tendency as published by Weun, Jones, and Beatty in 1997 [WJB97]
- Scepticism towards Advertising as published by Obermiller and Spangenberg in 1998 [OS98].

- Consumer Involvement Profiles (CIP) as published by Kapferer and Laurent in 1986 [KL86].
- Domain–Specific Innovativeness (DSI) as published by Goldsmith and Hofacker in 1991 [GH91].
- Opinion Leaders and Opinion Seekers as published by Flynn, Goldsmith and Eastman in 1996 [FGE96].

The original scales were translated into German. To avoid adulteration, the measures were translated by the author, retranslated by an independent translator and finally verified by an independent native speaker. These factors are measured along a seven–point Likert scale ranging from "totally disagree" to "totally agree".

The rest of the scales used in the research model (i.e. interest in personalized book recommendations, interest in writing book–related reviews, interest in reading book–related reviews, experience with online shopping, and privacy concerns) were developed by the author of the book. In accordance with the scales taken from literature, a seven–point Likert scale was used for measurement.

In Figure 4.4 the research design of this book is illustrated. In the first step a literature research was conducted and the problem statement defined. Based on that, the research model and the corresponding hypotheses set forth in this chapter were elaborated. The next stage included the development of the web–based questionnaire. As mentioned a translation– and retranslation–process was initiated to reduce adulteration due to language aspects.

After a pre–test phase (which included six persons) the first survey was conducted. This survey was performed in collaboration with the Austrian bookseller A&M Andreas & Dr. Müller Verlagsbuchhandel (www.aum.at). According to the Austrian Internet Radar A&M is on position number eighteen of Austrian web–sites with respect to the range of coverage. 16% of the Austrian Internet users in the sample have visited this web–site "within the last four weeks" (starting from the time of questioning, survey period: 2005-09-15 to 2005-12–15, n=5000) [AIR05]. For comparison, the world's biggest online

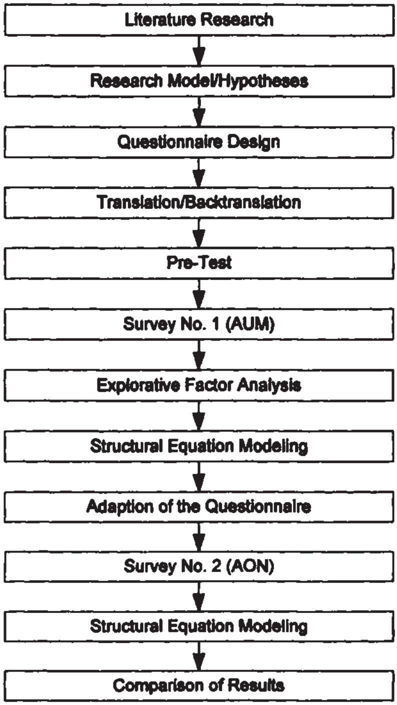


Figure 4.4: Research design

bookseller Amazon is on position number seven of Austria's most visited websites with a coverage of 34% [AIR05]. The survey was conducted from July 8th 2005 to September 2nd 2005.

In the next step, an exploratory factor analysis was conducted. The goal of this analysis was to shorten the questionnaire for the next survey and to determine the items that should be included in the structural equation model. To avoid fitting the model to the data (which would happen if the structural equation model was calculated on the whole dataset), the dataset was split. 20% of the data was used for an exploratory factor analysis. In this context, the three items of the scale with the highest factor loadings were chosen to be included into the structural equation model (the calculation was based on the remaining

80% of the data) and the construction of the questionnaire for the follow–up survey (i.e. the other items with lower loadings were removed from the original questionnaire).

The follow-up survey was conducted in cooperation with the biggest Austrian Internet service provider Telekom Austria AG (www.aon.at). According to the Austrian Internet Radar the Telekom Austria AG is on position number three of the Austrian web–sites with a coverage of 45%. The reasoning behind the follow–up survey was to analyze the two samples in regard to the differences. The results that stem from survey posted at the web–site of a bookseller are clearly of highest relevance for the purposes of this book, especially with respect to the composition of the sample. However, a survey posted at the web–site of an Internet service provider should be a good supplement, because the resulting sample is thought to represent the Austrian Internet population as a whole. To sum things up, the author assumes that the results derived from the first survey stand for typical Austrian "online shoppers with an interest in books", whereas the results from the second survey stand for the "general Austrian Internet population".

Chapter 5

Results

In this chapter, the empirical results are presented. In Section 5.1 the descriptive results (i.e. results that are not related to the hypotheses and the research model respectively) are illustrated. In this context, the sample size and demographic data are described. Further, results in regard to Internet usage, online shopping, product recommendations, ratings and comments are depicted. Section 5.2 deals with the the verification of the research model and the hypotheses. A factor analysis, a structural equation model that tests the psychographic hypotheses, and regression models that verify further psychographic and sociodemographic hypotheses are depicted.

As mentioned in Section 4.3 two independent surveys were conducted. The first survey was made in cooperation with the Austrian bookseller A&M Andreas & Dr. Müller Verlagsbuchhandel (www.aum.at). Results of this survey are hereinafter referred to as AUM. The second survey was conducted in cooperation with the Internet service provider Telekom Austria AG (www.aon.at). For results of this survey the acronym AON is used in the subsequent sections.

5.1 Descriptive Results

In the following, the descriptive results are set out. Firstly, a presentation of the sample size and the demographic data of the two surveys is undertaken.

Hereinafter, results of the Internet usage followed by descriptive results in respect to online shopping, online product recommendations, as well as ratings and comments are shown.

5.1.1 Sample Size and Demographic Data

The survey AUM was conducted from July 8th 2005 to September 2nd 2005. In total 682 participants filled out the questionnaire on the booksellers web-site. Survey AON was conducted from November 21st 2005 to December 5th 2005. In this survey 396 respondents were involved.

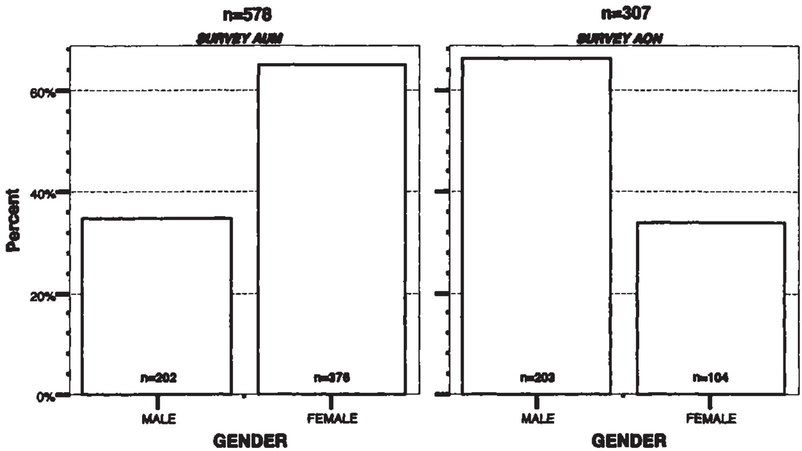


Figure 5.1: Sample description: Gender

Table 5.1: Sample description: Gender

GENDER	AUM	Frequency	Percent	Valid Percent	Austrian Internet Users	Deviation
Valid	MALE	202	29.62	34.95	55.00	-20.05
	FEMALE	376	55.13	65.05	45.00	20.05
	Total	578	84.75	100.00		
Missing	System	104	15.25			
Total		682	100.00			
GENDER	AON	Frequency	Percent	Valid Percent	Austrian Internet Users	Deviation
Valid	MALE	203	51.26	66.12	55.00	11.12
	FEMALE	104	26.26	33.88	45.00	-11.12
	Total	307	77.53	100.00		
Missing	System	89	22.47			
Total		396	100.00			

Figure 5.1 and Table 5.1 compare the two surveys in respect to the gender of the survey participants. 34.5% of the study participants of survey AUM (i.e. the survey conducted in cooperation with the bookseller) are male and 65,05% are female. Table 5.1 points out that 104 respondents refused to specify their gender. In this context the general proportion of male and female in the Austrian Internet user population is of interest. According to the GfK Online Monitor for the 3rd quarter 2005, 55% of the Austrian Internet user are male and 45% are female [GfK05]. As shown in Table 5.1, women are overrepresented by 20.05 percentage points in the sample AUM. In contrast in the survey AON (i.e. the survey posted on the web–site of the Internet service provider) woman are underrepresented by 11.12 percentage points. In this survey 66.12% of participants are male and 33.88% are female.

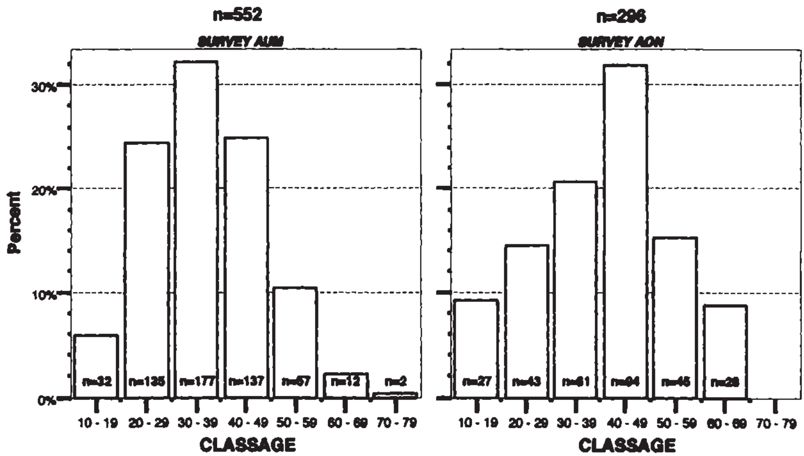


Figure 5.2: Sample description: Age pattern

Table 5.2: Mann–Whitney test: Age

Ranks

	SURVEY	N	Mean Rank	Sum of Ranks
RESPOAGE	SURVEY AUM	552	397.79	219579
	SURVEY AON	296	474.31	140397
	Total	848		

Test Statistics

	RESPOAGE
Mann-Whitney U	66951
Wilcoxon W	219579
Z	-4.34
Asymp. Sig. (2-tailed)	0.00

Figure 5.2 shows the age pattern of the two samples. In the survey AUM the youngest participant is 13 years old, the oldest has an age of 78. The arithmetic mean of age accounts for 36.2 years. More specifically, the arithmetic mean for men is 40.0 years, the arithmetic mean for women is 33.7. In the survey AON the minimum age is 12 years and the maximum is 69 years. The arithmetic mean in this survey accounts for 39.85 years. In this sample, the arithmetic mean for man is 42.5 years and the arithmetic mean for woman is 34.4 years. As shown in Table 5.2 the differences in respect to the age (RESPOAGE) of participants between the two samples are significant ($\alpha = 0.05$). The non–parametric Mann–Whitney test was performed, because normal distribution of the variable age was not given in the two samples.

Table 5.3: Sample description: Age pattern

AGE	AUM	Frequency	Percent	Valid Percent	Austrian Internet Users	Deviation
Valid	10 - 19	32	4.69	5.80	15.00	-9.20
	20 - 29	135	19.79	24.46	16.00	8.46
	30 - 39	177	25.95	32.07	26.00	6.07
	40 - 49	137	20.09	24.82	22.00	2.82
	50 - 59	57	8.36	10.33	13.00	-2.67
	60 - 69	12	1.76	2.17	7.00	-4.83
	70 - 79	2	0.29	0.36	1.00	-0.64
	Total	552	80.94	100.00	100.00	
Missing	System	130	19.06			
Total		682	100.00			
AGE	**AON**	**Frequency**	**Percent**	**Valid Percent**	**Austrian Internet Users**	**Deviation**
Valid	10 - 19	27	6.82	9.12	15.00	-5.88
	20 - 29	43	10.86	14.53	16.00	-1.47
	30 - 39	61	15.40	20.61	26.00	-5.39
	40 - 49	94	23.74	31.76	22.00	9.76
	50 - 59	45	11.36	15.20	13.00	2.20
	60 - 69	26	6.57	8.78	7.00	1.78
	70 - 79	0	0.00	0.00	1.00	-1.00
	Total	296	74.75	100.00	100.00	
Missing	System	100	25.26			
Total		396	100.00			

Table 5.3 compares the age patterns of both surveys to the age pattern of the general Austrian Internet population in the 3rd quarter of 2005. As shown in both surveys young and elderly people are underrepresented. Additionally the deviation from the general Internet population in Austria is depicted in percentage points for each class [GfK05].

The boxplots in Figure 5.3 summarizes the distribution of age with respect to the gender and highlights that women in both samples are on the average younger than male participants.

Figure 5.4 illustrates the occupation of the respondents of both surveys. In survey AUM the majority (46.8%) are white–collar employees, followed by pub-

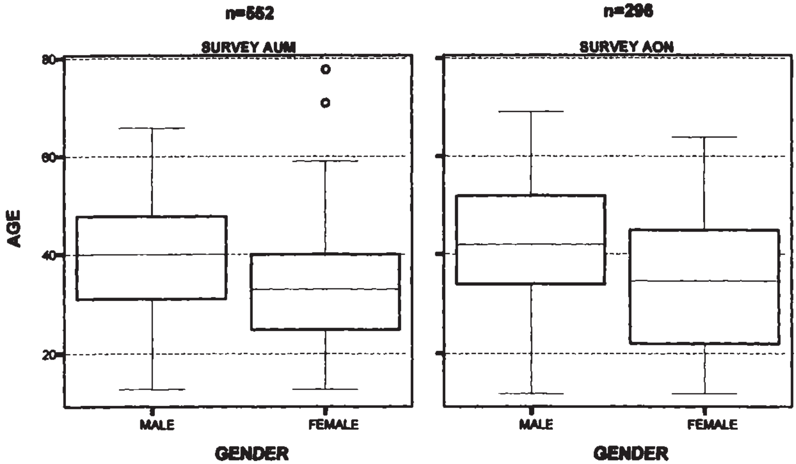


Figure 5.3: Sample description: Age by gender

lic servants (13%) and blue–collar employees (7.9%). 111 survey participants rejected to answer the question regarding the occupation. In survey AON white-collar employees are also the largest group (39,7%). To be consistent with study AUM, public servants constitute the second largest group (12.5%). In contrast to the first survey, retirees are the 3rd largest group (9.4%). Further, the percentage of blue–collar workers is equal to the self–employed people (8.1%). In this survey 99 persons did not answer the question regarding the occupation.

The educational levels of the respondents are depicted in Figure 5.5. In survey AUM, the two largest groups are survey participants with a final apprentice examination (30.1%) as well as respondents, who have attended a secondary school and received a diploma qualifying for university entrance (29.4%). 14.3% of the respondents possess an university degree. People who attended primary school solely account for 10.6%. 15.5% attended other educational institutions. 108 respondents did not answer the question regarding the educational level. In survey AON the overall educational level is slightly higher. The leading group consists of people, who attended a secondary school and received a diploma qualifying for university entrance (34.1%) followed by people with a final apprentice examination (30.1%). In contrast to the first

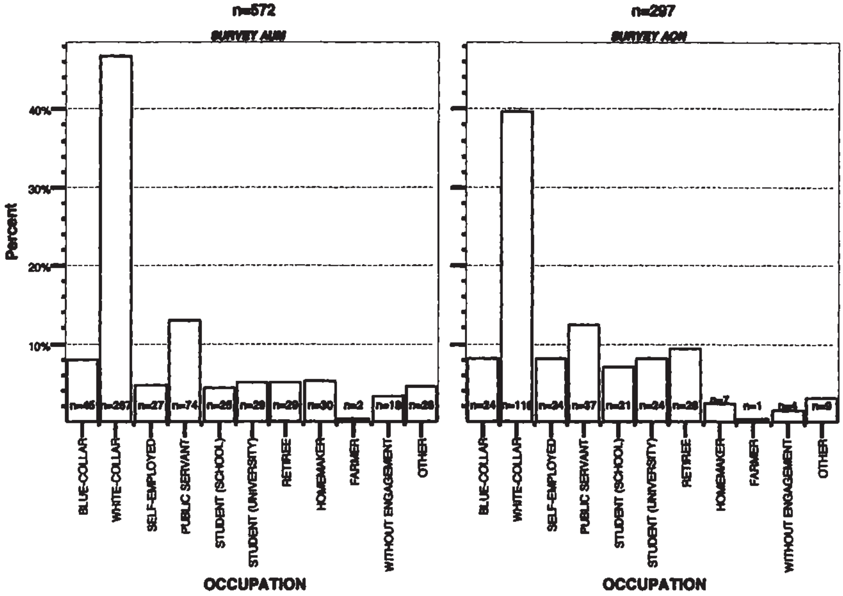


Figure 5.4: Sample description: Occupation

study people with a university degree form the third largest group. In survey AON 94 persons left out the question regarding their educational level.

Figure 5.6 compares the number of people in household for both surveys. 26.4% of the people in survey AUM live in households with 3 persons. 25.3% live in households with 2 persons followed by 21%, where the number of people in household is 4. Single households account for 12.7% in this survey. The largest household in respect to the number of persons is 8. In survey AON households with two persons (27.2%) are in the majority followed by households with 4 persons (25.5%). The leading group of survey AUM (i.e. households with 3 persons) are the third largest group in survey AON (21.1%). Interestingly, single households are less frequent than households with 5 persons. They account for 10.5%, whereas households with 5 persons account for 12.2%. In accordance with the first survey, the maximum number of people in a household is 8. In survey AUM 148 persons did not specify the number of persons in household. In survey AON 102 values are missing.

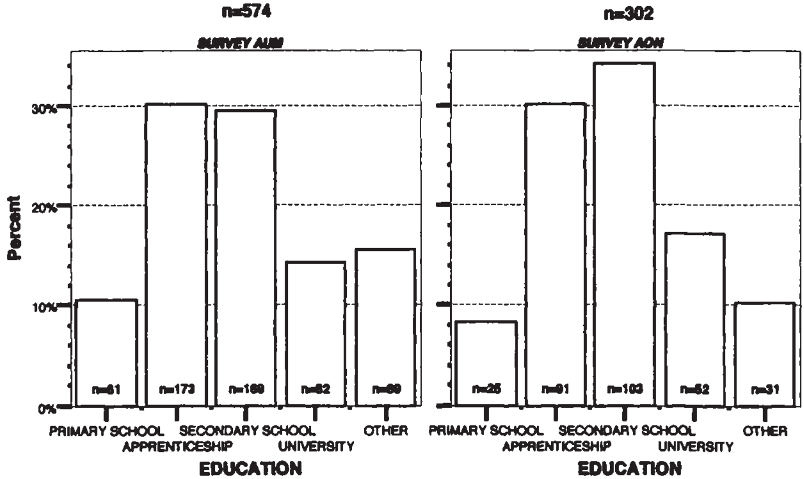


Figure 5.5: Sample description: Education

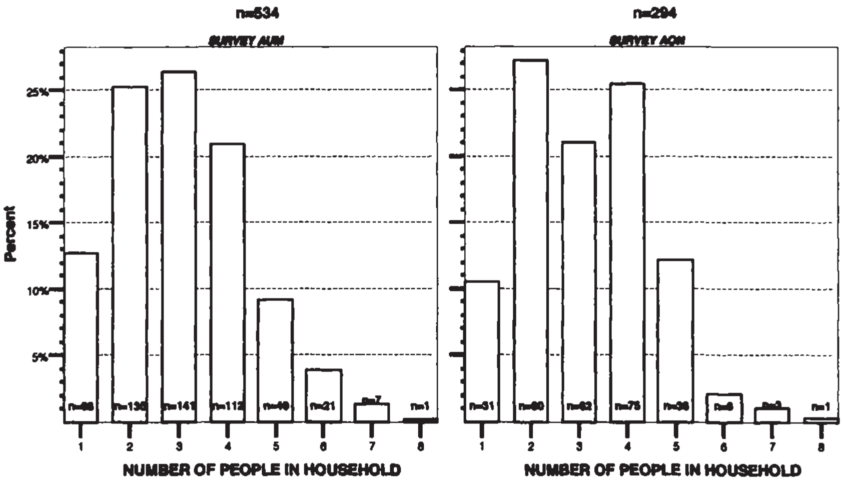


Figure 5.6: Sample description: Number of people in household

The monthly household income of the respondents is shown in Figure 5.7. In general the respondents where very reluctant to give this information. In survey AUM 47.80% of the overall sample (i.e. 61.16% of the valid responses)

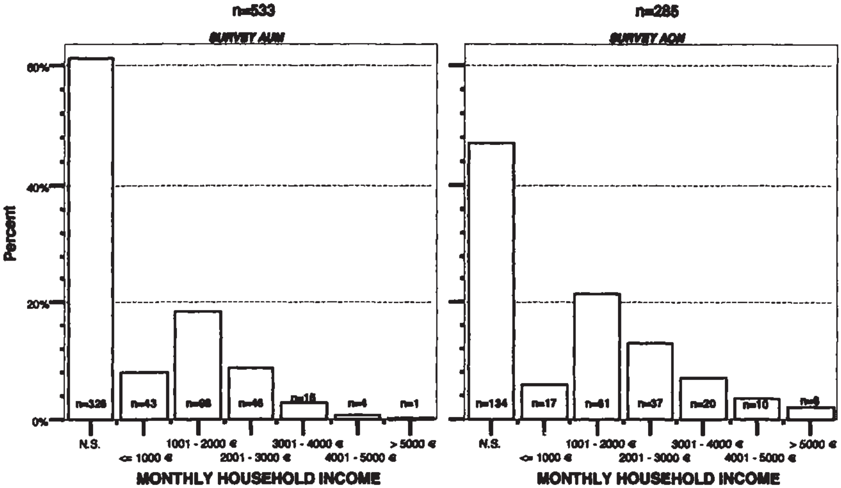


Figure 5.7: Sample description: Monthly household income

explicitly refused to specify this by marking the relevant field (i.e. "not specified") in the questionnaire. In addition, in 149 cases the respondents did not fill out this question at all. The largest group (14.37%) that specified the monthly household income has between 1001 € and 2000 € at disposal. The monthly household income of the second largest group (6,74%) is between 2001 € and 3000 €. 6,3% of the respondents have less or equal than 1000 € per month. The situation in survey AON is nearly identical. The majority (47%) of the respondents marked "not specified" in the questionnaire. In accordance with survey AUM people with a monthly household income between 1001 € and 2000 € form the largest group that has specified the income (21.4%). In contrast the third largest group are people with an income between 3001 € and 4000 €, whereas in survey AUM the third group that specified the income are people with an income below or equal 1000 €. In the second survey 111 values regarding the monthly household income are missing.

5.1.2 Internet Usage

The following section deals with the presentation of descriptive results in respect of the Internet usage.

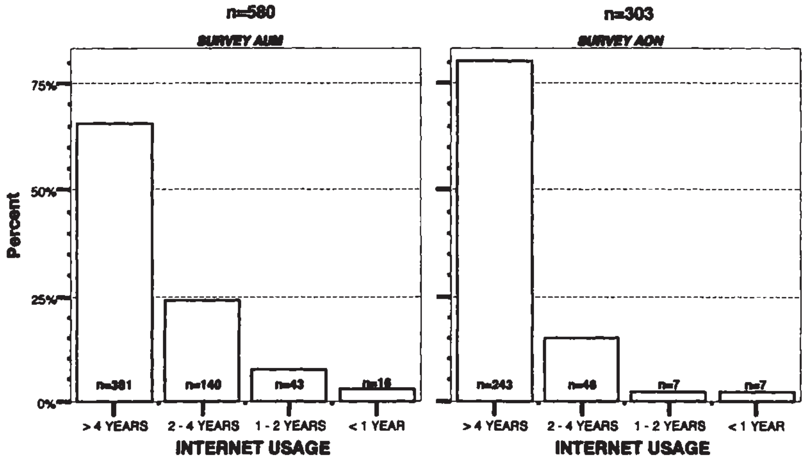


Figure 5.8: Sample description: Internet usage in years

As illustrated in Figure 5.8 in both surveys the majority has used the Internet for more than 4 years. In survey AUM this group accounts for 80.2%. 24.1% of the users in this survey have browsed the Internet for between 2 and 4 years, followed by 7.4%, who have used the Internet for between 1 and 2 years. 2.3% are relatively new to the Internet. They have experienced the Internet for less than 1 year. 102 respondents did not fill out their experience with the Internet in terms of years using it. In survey AON 80.2% have used the Internet for more than 4 years. 15.2% used the Internet for between 2 or 4 years. The both last groups in this survey account for 2.3% each. 93 values regarding Internet experience in years were missing in survey AON.

The average time in hours spent surfing on the Internet is illustrated for both surveys in the histograms of Figure 5.9. The boxplots below show the distribution of values in both surveys. In survey AUM, the respondents spent 12.96 hours on average per week on the Internet, whereas in the survey AON the arithmetic mean accounts for 15.33 hours.

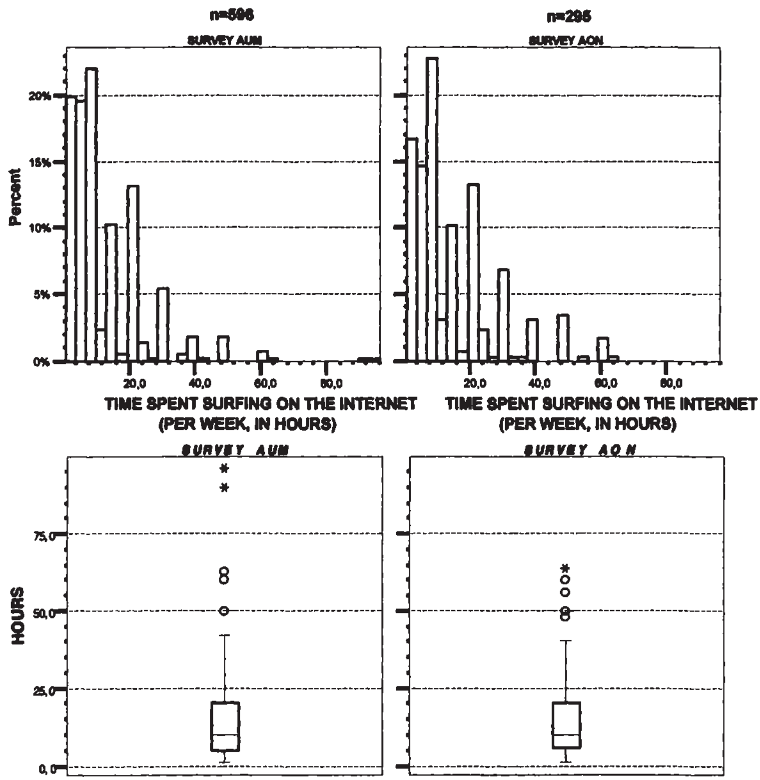


Figure 5.9: Sample description: Time spent on the Internet (weekly, in hours)

According to the Mann-Whitney test shown in Table 5.4 the differences in regard to the time spent online (INTEHOUR) between the two surveys are significant ($\alpha = 0.05$). Additionally, gender–related differences of time spent browsing the Internet for both surveys were investigated. As shown in Table 5.5 no significant differences ($\alpha = 0.05$) between males and females in respect of the time spent online were found in the two surveys.

Figure 5.10 illustrates from which places people have access to the Internet. Multiple answers are possible in this question. In survey AUM, 78.7% of the respondents have access to the Internet from their home. 38.4% may

Table 5.4: Mann-Whitney test: Time spent on the Internet

Ranks

	SURVEY	N	Mean Rank	Sum of Ranks
INTEHOUR	SURVEY AUM	569	416.80	237158.50
	SURVEY AON	295	462.78	136521.50
	Total	864		

Test Statistics

	INTEHOUR
Mann-Whitney U	74993.5
Wilcoxon W	237158.5
Z	-2.58
Asymp. Sig. (2-tailed)	0.01

Table 5.5: Mann–Whitney test: Time spent on the Internet by Gender

Ranks

AUM	GENDER	N	Mean Rank	Sum of Ranks
INTEHOUR	MALE	196	299.93	58783.50
	FEMALE	368	373.22	100546.50
	Total	564		

AON	GENDER	N	Mean Rank	Sum of Ranks
INTEHOUR	MALE	195	150.41	29329.00
	FEMALE	100	143.31	14331.00
	Total	295		

Test Statistics

	AUM INTEHOUR	AON INTEHOUR
Mann-Whitney U	32650.50	9281.00
Wilcoxon W	100546.50	14331.00
Z	-1.86	-0.68
Asymp. Sig. (2-tailed)	0.06	0.50

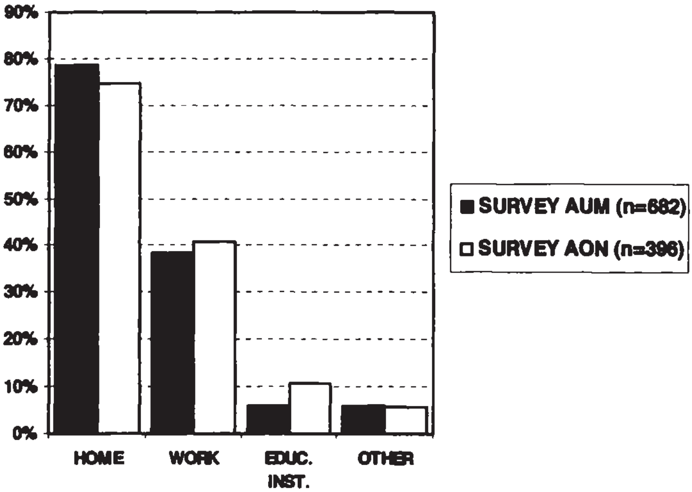


Figure 5.10: Sample description: Access to the Internet

utilize the Internet from their workplace. 6.0% have access from educational institutions and 6.2% access the Internet from other places. The situation in survey AON is very similar. 74.5% use the Internet at home, 40.7% use it from the workplace, 10.6% from home, 10.6% access the Internet from educational institutions. 5.8% utilize the Internet from other places.

5.1.3 Online Shopping

In this section Internet shopping related questions of the surveys are discussed.

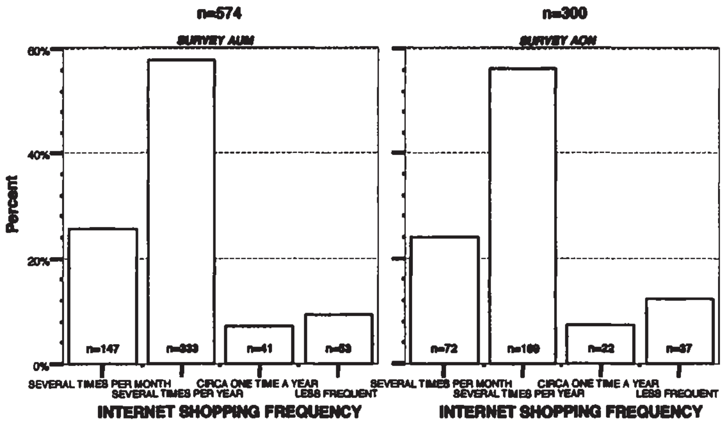


Figure 5.11: Sample description: Internet shopping frequency

In Figure 5.11, the Internet shopping frequencies of the two surveys are compared. In survey AUM, 25.6% of the survey participants buy online several times per month. The majority (58.0%) of the valid responses purchase online several times per year. 7.1% shop circa one time a year and 9.2% buy less frequent. In 108 cases, the specification of the shopping frequency is missing. In survey AON the situation is nearly identical. 24.0% of the respondents buy several times per month. 42.7% shop several times per year, followed by 7.3%, who acquire products and services online circa one time a year. 12.3% buy less frequent. 96 respondents did not answer this question.

In this context, differences in the shopping frequency in respect to gender, time spent on the Internet and age were investigated. According to the non-parametric Mann-Whitney test shown in Table 5.6 no significant differences in the shopping frequency (FREQSHOP) were found between men and women in both samples.

Table 5.6: Mann–Whitney test: Internet shopping frequency by gender

Ranks				
AUM	GENDER	N	Mean Rank	Sum of Ranks
FREQSHOP	MALE	196	299.48	58698.50
	FEMALE	373	277.39	103466.50
	Total	569		
AON	GENDER	N	Mean Rank	Sum of Ranks
FREQSHOP	MALE	201	146.93	29532.50
	FEMALE	99	157.75	15617.50
	Total	300		

Test Statistics	AUM FREQSHOP	AON FREQSHOP
Mann-Whitney U	33716.50	9231.50
Wilcoxon W	103466.50	29532.50
Z	-1.72	-1.13
Asymp. Sig. (2-tailed)	0.09	0.26

Regarding the age of respondents and time spent on the Internet a bi–variate correlation analysis (Spearman's rho) was performed. Table 5.7 shows that no significant relationship between shopping frequency and age (RESPOAGE) of the respondents was found. The relationship between time spent on the Internet (INTEHOUR) and buying frequency is of high significance ($\alpha = 0.05$) in both surveys. The correlation coefficient is negative because of the reversed coding of shopping frequency (i.e. 1 means a high frequency, 4 means a low frequency). Hence, people that spent a lot of time on the Internet also have a higher buying frequency, which is pretty obvious.

Table 5.7: Bi–variate correlation analysis: Internet shopping frequency, age and time spent on the Internet

Correlations			AUM FREQSHOP	AON FREQSHOP
Spearman's rho	RESPOAGE	Correlation Coefficient	0.08	0.10
		Sig. (2-tailed)	0.07	0.08
		N	544	290
	INTEHOUR	Correlation Coefficient	-0.18	-0.18
		Sig. (2-tailed)	0.00	0.00
		N	564	292

The online shopping frequency of books of the two surveys is illustrated in Figure 5.12. The respondents were asked to answer this question on a seven point Likert scale ranging from never (value = 1) to very frequent (value =

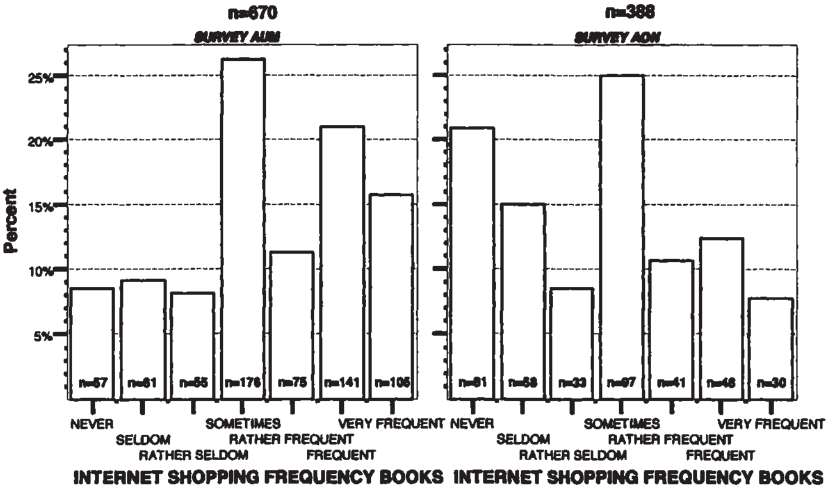


Figure 5.12: Sample description: Internet shopping frequency of books

7). As the bar chart shows, the situation is quite different in both surveys. Although in both surveys the majority buys books "'sometimes" (i.e. 26.3% in survey AUM, 25.0% in survey AON), in the other categories the two surveys differ substantially. In survey AUM "heavy buyers" (i.e. consumers that buy books more often than "sometimes" are dominant, whereas survey AON exhibits buyers predominantly, who buy books less frequently than "sometimes". These results are quite obvious, because survey AUM was posted on the web site of a bookseller, whereas survey AON was posted on the web site of an Internet service provider. In survey AUM the arithmetic mean is 4.48, in survey AON the arithmetic mean of the book–related buying frequency is 3.57. In survey AUM, the number of missing values accounts for 12, whereas in survey AON 8 respondents did not fill out this question.

In Figure 5.13 the shopping frequency of music in the two surveys is compared. In general music is more seldom purchased than books in both surveys. The arithmetic mean in survey AUM is 3.53 (compared to 4.58 in the book category). In contrast to the category books, the number of people that buy music less frequently than "sometimes" outweigh the "heavy buyers" (i.e. consumer that buy music more frequently than "sometimes"). Although, the majority

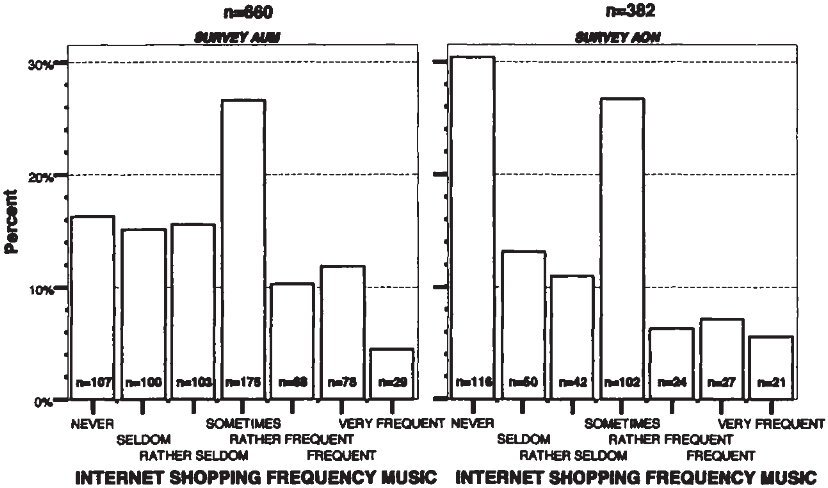


Figure 5.13: Sample description: Internet shopping frequency of music

(26.5%) "sometimes" buys music. In contrast, in survey AON the most people (30.4%) "never" buy music, followed by people who "sometimes" buy music online (26.7%). The arithmetic mean accounts for 3.09 (compared to 3.57 in the book category). The number of missing values in this category is 22 (AUM) and 14 (AON).

As Figure 5.14 illustrates, movies is the least sold product category in both surveys. In survey AUM, the percentage of people that "never" (22.3%) buy movies is nearly equal to the percentage of people that sometimes (22.7%) buy movies. The arithmetic mean in this survey accounts for 3.22. In survey AON, consumers that never buy movies are by far the dominant group (41.6%). The arithmetic mean adds up to 2.58. The number of missing values is 27 in survey AUM and 19 in survey AON respectively.

The shopping frequencies of this three product categories reflect the results of the Austrian Internet Monitor in the third quarter of 2005 [AIM05]. In this study the top 10 of products sold over the Internet are presented. The number one product category is represented by books (37% of the Austrian Internet user have bought a book in the last three months) followed by clothing and

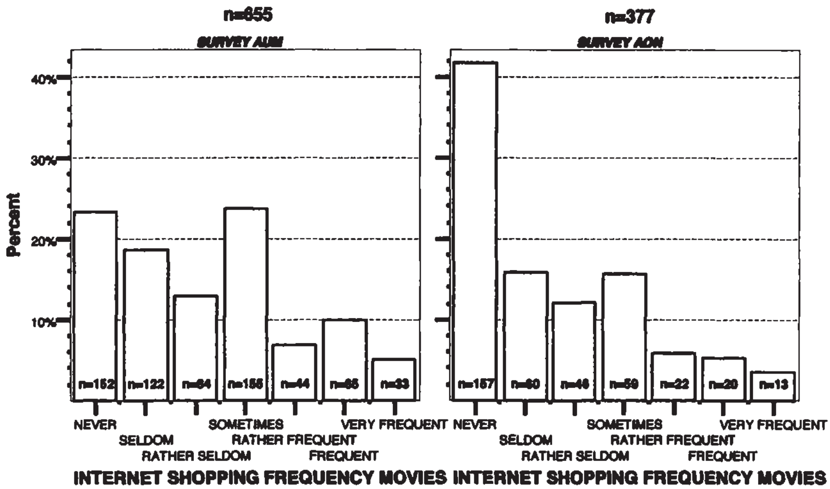


Figure 5.14: Sample description: Internet shopping frequency of movies

shoes. Music is the 5th most sold product (14%), whereas movies are on place 8 of the list (9%).

Two Mann-Whitney tests were performed to investigate gender specific differences of buying frequencies. The results are presented in Table 5.8 and Table 5.9. FREQBOOK refers to the buying frequency of books, FREQMUSI to the frequency of music and FREQMOVI to the frequency of movies. Interestingly for the product categories music and movies no significant differences between male and female respondents were found in both surveys ($\alpha = 0.05$). On the other hand books are significantly more often bought by women in both surveys ($\alpha = 0.05$).

In Table 5.10 a bivariate correlation analysis (Spearman's rho) for each product category is shown. In the following interpretation of the correlation analysis a significance level of 0.05 is assumed (i.e.$\alpha = 0.05$).

In survey AUM, the product category book shows no significant relationship between age and buying frequency of books. Further, no significant correlation between time spent on the Internet and buying frequency exists according to the survey. In contrast, in survey AON a significant correlation between time

Table 5.8: Mann–Whitney test survey AUM: Internet shopping frequency of books, music and movies by gender

Ranks

	GENDER	N	Mean Rank	Sum of Ranks
FREQBOOK	MALE	196	248.22	48651.50
	FEMALE	374	305.04	114083.50
	Total	570		
FREQMUSI	MALE	193	275.50	53172.00
	FEMALE	364	280.85	102231.00
	Total	557		
FREQMOVI	MALE	192	279.03	53573.50
	FEMALE	362	276.69	100161.50
	Total	554		

Test Statistics

	FREQBOOK	FREQMUSI	FREQMOVI
Mann-Whitney U	29345.50	34451.00	34458.50
Wilcoxon W	48651.50	53172.00	100161.50
Z	-3.98	-0.38	-0.17
Asymp. Sig. (2-tailed)	0.00	0.70	0.87

Table 5.9: Mann–Whitney test survey AON: Internet shopping frequency of books, music and movies by gender

Ranks

	GENDER	N	Mean Rank	Sum of Ranks
FREQBOOK	MALE	199	143.83	28622.00
	FEMALE	103	166.32	17131.00
	Total	302		
FREQMUSI	MALE	196	151.29	29653.00
	FEMALE	102	146.06	14898.00
	Total	298		
FREQMOVI	MALE	195	148.12	28883.50
	FEMALE	102	150.68	15369.50
	Total	297		

Test Statistics

	FREQBOOK	FREQMUSI	FREQMOVI
Mann-Whitney U	8722.00	9645.00	9773.50
Wilcoxon W	28622.00	14898.00	28883.50
Z	-2.16	-0.51	-0.25
Asymp. Sig. (2-tailed)	0.03	0.61	0.80

spent on the Internet and buying frequency of the product category book is found.

The buying frequency of music has a significant positive relationship with the time spent on the Internet in both surveys. In respect to the age of the respondents no significant correlation was detected in both surveys.

Interestingly, the buying frequency of movies has a significant negative relationship with the age of the respondents. Hence, it can be assumed that as a tendency movies are bought by younger people. Additionally, a significant positive relationship between time spent on the Internet and the buying frequency of movies is found in both surveys.

For the correlation analysis of education and shopping frequencies of the three

Table 5.10: Bi–variate correlation analysis: Internet shopping frequency of books, music and movies

Correlations			AUM FREQBOOK	AON FREQBOOK
Spearman's rho	INTEHOUR	Correlation Coefficient	0.07	0.15
		Sig. (2-tailed)	0.10	0.01
		N	562	290
	RESPOAGE	Correlation Coefficient	-0.06	-0.05
		Sig. (2-tailed)	0.20	0.44
		N	545	292
	EDUCATION	Correlation Coefficient	0.12	0.26
		Sig. (2-tailed)	0.01	0.00
		N	478	267
			AUM FREQMUSI	AON FREQMUSI
Spearman's rho	INTEHOUR	Correlation Coefficient	0.10	0.18
		Sig. (2-tailed)	0.02	0.00
		N	551	287
	RESPOAGE	Correlation Coefficient	0.07	-0.10
		Sig. (2-tailed)	0.13	0.10
		N	535	287
	EDUCATION	Correlation Coefficient	-0.02	-0.04
		Sig. (2-tailed)	0.65	0.54
		N	468	264
			AUM FREQMOVI	AON FREQMOVI
Spearman's rho	INTEHOUR	Correlation Coefficient	0.12	0.15
		Sig. (2-tailed)	0.00	0.01
		N	547	286
	RESPOAGE	Correlation Coefficient	-0.13	-0.20
		Sig. (2-tailed)	0.00	0.00
		N	534	286
	EDUCATION	Correlation Coefficient	-0.15	0.03
		Sig. (2-tailed)	0.00	0.63
		N	467	263

products types cases with the category "other" were excluded from the dataset to obtain a distinct ordinal measurement scale. As the table shows, in both surveys books are more often bought by people with a higher educational level. For the shopping frequency of music no significant relationship is detected in respect to the educational level of the respondents in both surveys. Regarding movies the results of the two surveys differ. Survey AUM shows a significant negative relationship, whereas survey AON shows now significant differences.

5.1.4 Online Product Recommendations

In this section descriptive results with respect to online product recommendations are presented.

Figure 5.15 contrasts the percentage of people that have got recommendations in e–commerce applications to people that have never received such recommendations. In survey AUM, 78.6% of the survey participants have already

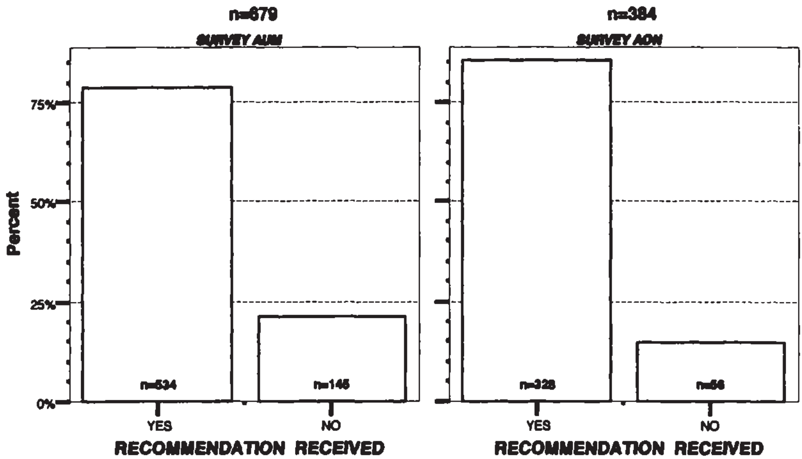


Figure 5.15: Sample description: Recommendation received

received a product recommendation in an online shop. 21.4% stated that they have never got a recommendation. At the time of the survey the online shop of the bookseller did not employ any kind of recommender system. In the second survey (AON) (i.e. the questionnaire posted at the web site of the Internet service provider), the percentage of people that have been exposed to online product recommendations is even higher (85.4%). Thence, 14.6% of the respondents have never got a recommendation in this survey. The number of people who did not answer this questions adds up to 3 in survey AUM and 12 in survey AON respectively.

In the following buying frequencies of books, music, and movies that were bought because of an online product recommendation are investigated. In the questionnaire the three questions were designed as filter questions. Hence, these questions were only displayed to people, who answered the question if they have already recieved product recommendations with "yes" (See Figure 5.15).

In Figure 5.16 the buying frequency of books that were bought because of a recommendation is illustrated. In both surveys the group of respondents that "sometimes" buys books because of a recommendation is leading (AUM 27.4%,

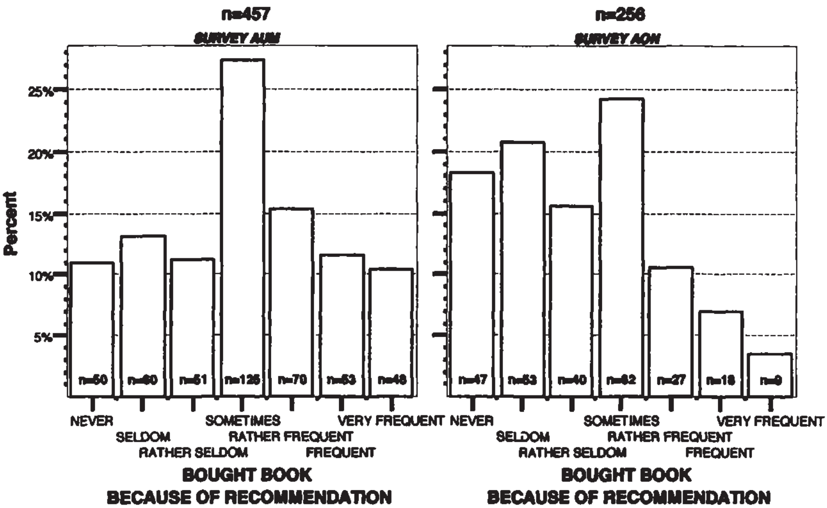


Figure 5.16: Sample description: Bought books because of recommendation

AON 24.2%). As shown in the bar chart in survey AUM the respondents that buy books more often than "sometimes" are predominant over respondents that buy less frequently than "sometimes". In survey AON, the situation is contrary. Therein, people that buy books less frequently than "sometimes" outweigh people that buy books more frequently than sometimes because of a given recommendation. The arithmetic mean for this question accounts for 4.00 in survey AUM and 3.23 in survey AON respectively.

Figure 5.17 illustrates the buying frequency of music due to recommendations in online shops. In survey AUM 26.0% of the respondents have "sometimes" bought music because of a recommendation, followed by 24.2%, who have "never" bought music due to a suggestion in an online store. In contrast, in survey AUM the majority (36.0%) has "never" bought music because of a recommendation. 23.3% have sometimes purchased a book because of this. In both surveys, the percentage of people that have bought music less frequently than sometimes outweighs the percentage of people that have bought music more frequently than sometimes. The arithmetic mean in survey AUM is 3.18. In the other survey the arithmetic mean accounts for 2.75.

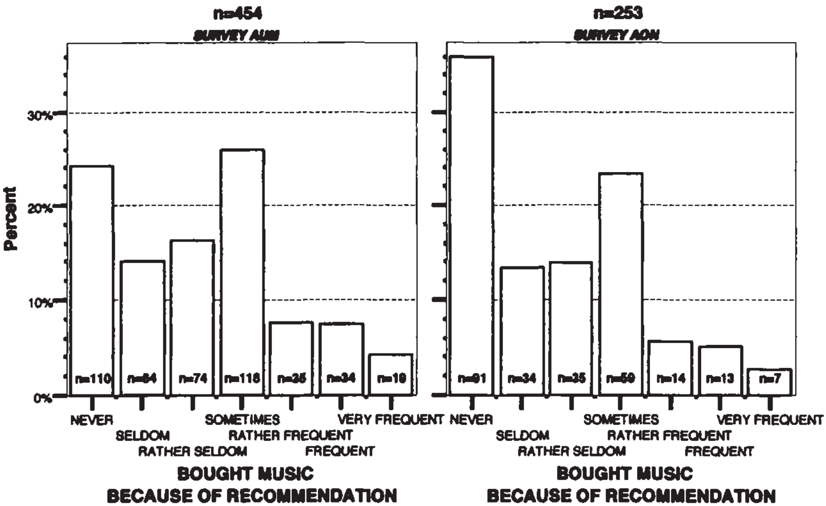


Figure 5.17: Sample description: Bought music because of recommendation

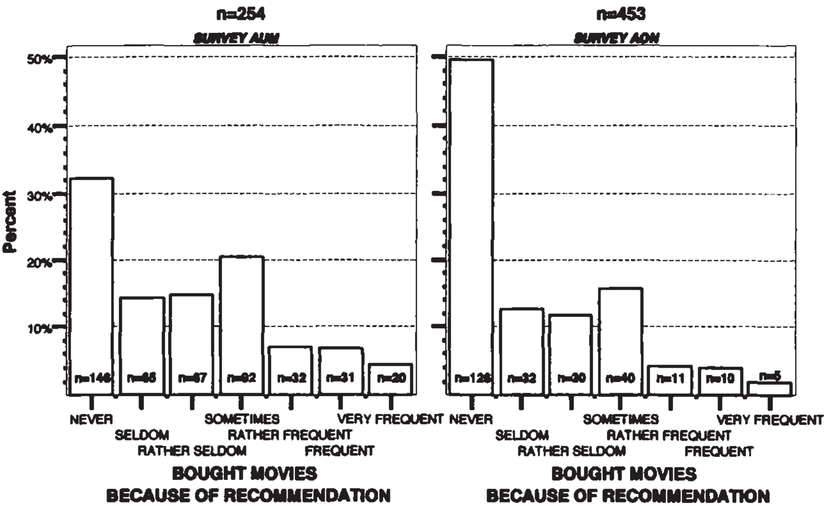


Figure 5.18: Sample description: Bought movies because of recommendation

As Figure 5.18 clearly shows that movies are the least frequent product category bought due to recommendations. In both surveys, the majority has "never" bought a movie because of a recommendation (32.2% in survey AUM and 49.6% in survey AON), followed by respondents that buy sometimes books (20.3% in survey AUM and 15.7% in survey AON). The arithmetic mean in survey AUM is 2.94 and 2.32 in survey AON respectively.

Table 5.11: Mann–Whitney test survey AON: Internet shopping frequency of books, music and movies bought because of recommendations by gender

Ranks	GENDER	N	Mean Rank	Sum of Ranks
FREQREBO	MALE	158	195.96	30961.50
	FEMALE	292	241.48	70513.50
	Total	450		
FREQREMU	MALE	157	216.81	34039.50
	FEMALE	290	227.89	66088.50
	Total	447		
FREQREMO	MALE	159	226.64	36035.00
	FEMALE	287	221.76	63646.00
	Total	446		

Test Statistics	FREQREBOOK	FREQREMUSI	FREQREMOVI
Mann-Whitney U	18400.50	21636.50	22318.00
Wilcoxon W	30961.50	34039.50	63646.00
Z	-3.60	-0.88	-0.39
Asymp. Sig. (2-tailed)	0.00	0.38	0.70

Table 5.12: Mann–Whitney test survey AUM: Internet shopping frequency of books, music and movies bought because of recommendations by gender

Ranks	GENDER	N	Mean Rank	Sum of Ranks
FREQREBO	MALE	166	125.16	20776.50
	FEMALE	86	129.09	11101.50
	Total	252		
FREQREMU	MALE	164	132.11	21666.50
	FEMALE	85	111.28	9458.50
	Total	249		
FREQREMO	MALE	164	128.40	21057.00
	FEMALE	86	119.98	10318.00
	Total	250		

Test Statistics	FREQREBOOK	FREQREMUSI	FREQREMOVI
Mann-Whitney U	6915.50	5803.50	6577.00
Wilcoxon W	20776.50	9458.50	10318.00
Z	-0.41	-2.24	-0.94
Asymp. Sig. (2-tailed)	0.68	0.03	0.35

As Table 5.11 and Table 5.12 show, the two studies deliver a rather inconsistent picture of differences between male and female respondents in respect of the shopping frequency of books (FREQREBOOK), music (FREQREMUSI) and movies (FREQREMOVI) due to recommendations. In survey AUM, women buy books significantly more often because of recommendations. In survey AON, books are also more often bought by women because of recommendations (mean rank of male respondents is 125.16 vs. 129.09 of female respondents).

However, this relationship is not significant. On the other side, in survey AON a significant positive relationship between male survey participants and the frequency of buying music by reason of recommendations is detected, which is not the case in survey AUM.

Table 5.13: Bi–variate correlation analysis: Internet shopping frequency of books, music and movies because of recommendations

Correlations			AUM FREQREBOOK	AON FREQBOOK
Spearman's rho	INTEHOUR	Correlation Coefficient	0.13	0.11
		Sig. (2-tailed)	0.00	0.08
		N	446	242
	RESPOAGE	Correlation Coefficient	-0.12	-0.10
		Sig. (2-tailed)	0.02	0.12
		N	432	244
	EDUCATION	Correlation Coefficient	0.10	0.11
		Sig. (2-tailed)	0.06	0.11
		N	376	223
			AUM FREQREMUSI	AON FREQREMUSI
Spearman's rho	INTEHOUR	Correlation Coefficient	0.17	0.20
		Sig. (2-tailed)	0.00	0.00
		N	443	239
	RESPOAGE	Correlation Coefficient	0.05	-0.14
		Sig. (2-tailed)	0.30	0.03
		N	430	241
	EDUCATION	Correlation Coefficient	-0.04	-0.11
		Sig. (2-tailed)	0.39	0.09
		N	374	220
			AUM FREQREMOVI	AON FREQREMOVI
Spearman's rho	INTEHOUR	Correlation Coefficient	0.18	0.20
		Sig. (2-tailed)	0.00	0.00
		N	441	240
	RESPOAGE	Correlation Coefficient	-0.12	-0.24
		Sig. (2-tailed)	0.01	0.00
		N	430	242
	EDUCATION	Correlation Coefficient	-0.16	-0.06
		Sig. (2-tailed)	0.00	0.40
		N	373	220

Table 5.13 shows the results of the bi–variate correlation analysis of shopping frequency due to recommendations, time spent on the Internet, age, and educational level of the respondents. The time spent surfing on the Internet has a positive relationship with the shopping frequency of the three product categories except in one case, i.e. in survey AON the shopping frequency does not meet the desired significance level of 0.05 (as shown in the table "Sig." is 0.08). Regarding the age of the respondents, the two surveys only deliver an identical picture in the category movies. Younger people buy movies significantly more often because of recommendations in both surveys. As the table shows, the relationship between educational level and buying frequency of the three products is not well founded. Only in survey AUM, a significant negative relationship between these two factors is identified.

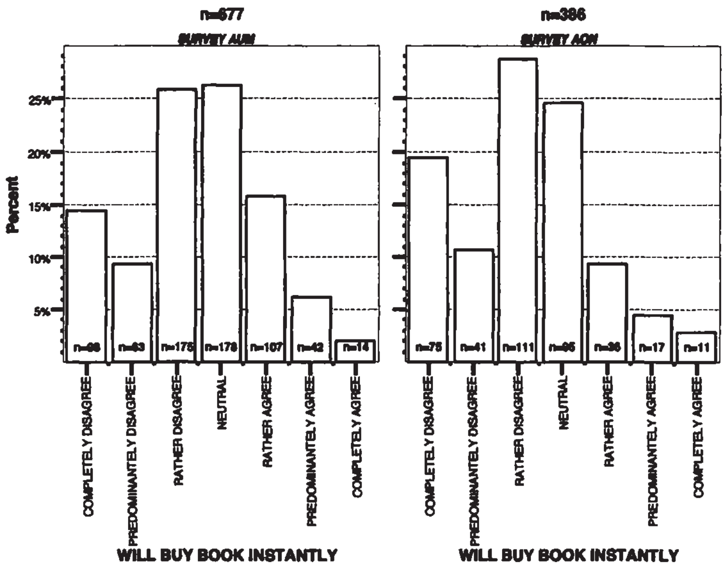


Figure 5.19: Sample description: "I would buy the recommended book instantly at the online–shop that has given a recommendation"

Table 5.14: Regression analysis survey AUM: Factors that influence "I would buy the recommended book instantly at online–shop that has given an interesting recommendation"

R	R Square	Adjusted R Square	Std. Error of the Estimate		
0.47	0.22	0.22	1.32		
ANOVA					
	Sum of Squares	df	Mean Square	F	Sig.
Regression	328.83	2	164.41	94.44	0.00
Residual	1159.52	666	1.74		
Total	1488.35	668			
COEFFICIENTS					
	B	Std. Error	Beta	t	Sig.
(Constant)	0.78	0.21		3.75	0.00
EXRECO	0.46	0.04	0.41	11.90	0.00
IMPUBU	0.17	0.03	0.17	5.05	0.00

The results in Figure 5.19 refer to the question if consumers would buy an interesting book recommended to them in an online shop. Respondents were asked for their level of consent to the hypothetical statement that they would instantly buy a book from an online–shop that has given an interesting book recommendation. This degree of consent is measured on a seven point Likert

Table 5.15: Regression analysis survey AON: Factors that influence "I would buy the recommended book instantly at online–shop that has given an interesting recommendation"

R	R Square	Adjusted R Square	Std. Error of the Estimate		
0.54	0.29	0.29	1.29		
ANOVA					
	Sum of Squares	df	Mean Square	F	Sig.
Regression	262.36	2	131.18	78.74	0.00
Residual	631.44	379	1.67		
Total	893.80	381			
COEFFICIENTS					
	B	Std. Error	Beta	t	Sig.
(Constant)	0.54	0.23		2.37	0.02
EXRECO	0.56	0.05	0.51	11.48	0.00
IMPUBU	0.11	0.04	0.12	2.71	0.01

scale ranging from totally disagree to totally agree. The overall tendency in both surveys is that the respondents rather disagree this statement. The arithmetic mean in survey AUM is 3.47 compared to 3.18 in survey AON.

Interestingly, the regression analyses in Table 5.14 and Table 5.15 present that the general impulse buying tendency (IMPUBU) and the positive past experience with online product recommendations (EXRECO) significantly determine the degree of agreement to the statement "I would buy the recommended book instantly at online–shop that has given an interesting recommendation". Hence, it can be said that people, who have a high impulse buying tendency and who have a positive past experience with online recommendations are more likely to buy recommended books instantly.

Table 5.16: Regression analysis survey AUM: Factors that influence "I would rather buy a recommended book in a bricks–and–mortar store"

R	R Square	Adjusted R Square	Std. Error of the Estimate		
0.56	0.31	0.31	1.32		
ANOVA					
	Sum of Squares	df	Mean Square	F	Sig.
Regression	513.56	3	171.19	98.91	0.00
Residual	1126.67	651	1.73		
Total	1640.23	654			
COEFFICIENTS					
	B	Std. Error	Beta	t	Sig.
(Constant)	6.31	0.38		16.62	0.00
TRUSSH	-0.21	0.05	-0.16	-3.98	0.00
EXSHOP	-0.45	0.04	-0.43	-11.96	0.00
PRIVCO	0.11	0.04	0.10	2.81	0.01

Figure 5.20 shows the results regarding the consent to the statement that they would rather buy a recommended book in a traditional bricks–and–mortar

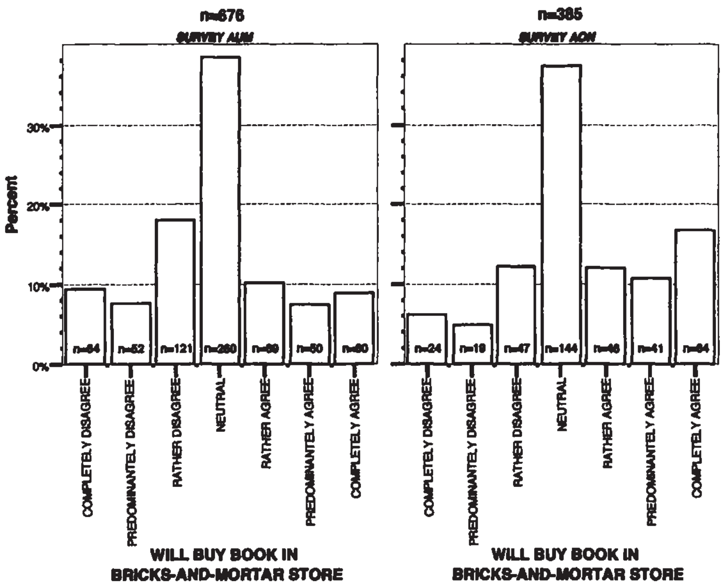


Figure 5.20: Sample description: "I would rather buy a recommended book in a bricks–and–mortar store"

Table 5.17: Regression analysis survey AON: Factors that influence "I would rather buy a recommended book in a bricks–and–mortar store"

R	R Square	Adjusted R Square	Std. Error of the Estimate		
0.48	0.23	0.22	1.47		
ANOVA					
	Sum of Squares	df	Mean Square	F	Sig.
Regression	237.07	3	79.02	36.47	0.00
Residual	801.69	370	2.17		
Total	1038.76	373			
COEFFICIENTS					
	B	Std. Error	Beta	t	Sig.
(Constant)	7.53	0.56		13.35	0.00
TRUSSH	-0.34	0.08	-0.25	-4.18	0.00
EXSHOP	-0.36	0.06	-0.33	-6.34	0.00
PRIVCO	-0.04	0.06	-0.03	-0.62	0.54

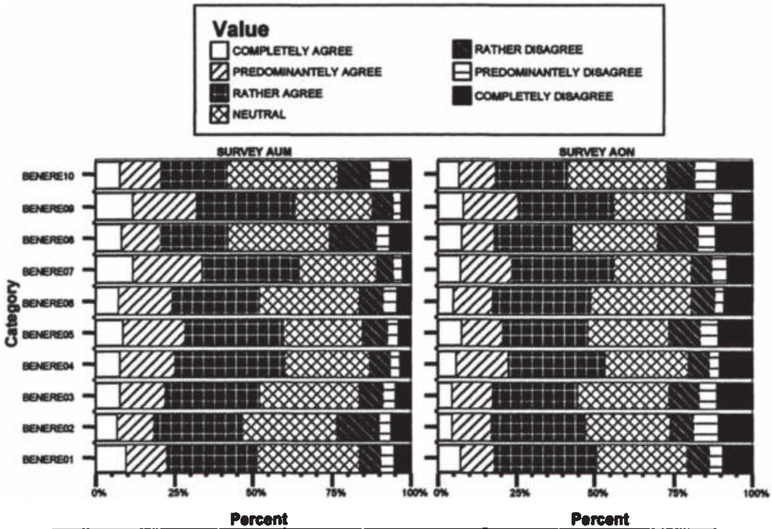
store. Again the underlying assumption is that they recieve a book recommendation from an online store and that they are interested in that recommended book. In both surveys, the majority adopts a neutral position (AUM 38.5%, AON 37.4%). In survey AUM the proportion of respondents that disagrees (i.e. people that answered "rather disagree", "predominantly disagree", or "completely disagree") is higher than the people that agree this statement (35.1% disagreement vs. 26.5% agreement). In survey AON, the opposite is the case (23.4% disagreement vs. 39.1% agreement). The arithmetic mean in survey AUM is 3.90 and 4.42 in survey AON respectively.

The regression analyses in Table 5.16 and Table 5.17 show the factors that influence the degree of consent to the statement "I would rather buy a recommended book in a bricks-and-mortar store". The author assumed that positive past experience with online shopping (EXSHOP), trust in online shopping (TRUSSH) and privacy concerns (PRIVCO) have an influence. As shown in both surveys both positive past experience with online shopping and trust in online shopping have a significant negative influence on the agreement to statement. In survey AUM, privacy concerns also seem to have an (positive) effect on the degree of acceptance of the statement. However, in survey AON no significant relationship is detected.

Table 5.18: Sample description: Benefits of recommendations

SURVEY AUM					
	BENERE01	BENERE02	BENERE03	BENERE04	BENERE05
Valid	456	456	457	455	457
Mean	4.53	4.31	4.52	4.70	4.70
Rank	6	8	7	4	3
	BENERE06	BENERE07	BENERE08	BENERE09	BENERE10
Valid	454	456	457	454	452
Mean	4.54	4.91	4.27	4.86	4.27
Rank	5	1	10	2	9
SURVEY AON					
	BENERE01	BENERE02	BENERE03	BENERE04	BENERE05
Valid	256	254	252	252	253
Mean	4.32	4.13	4.12	4.38	4.23
Rank	4	7	8	3	6
	BENERE06	BENERE07	BENERE08	BENERE09	BENERE10
Valid	255	255	254	255	253
Mean	4.31	4.46	4.09	4.50	4.10
Rank	5	2	10	1	9

Figure 5.21 illustrates the degree of consent of the respondents regarding the benefits of recommendations. Respondents were asked to answer this question on a seven point Likert scale ranging from totally disagree (1) to totally agree (7). The results refer to respondents that have already received recommendations. Table 5.18 shows that the respondents in both surveys agree that recommendations help to find new interesting products and call attention to low-priced products. They rather disagree that recommendations help to avoid mispurchases and ease navigation in online shops.



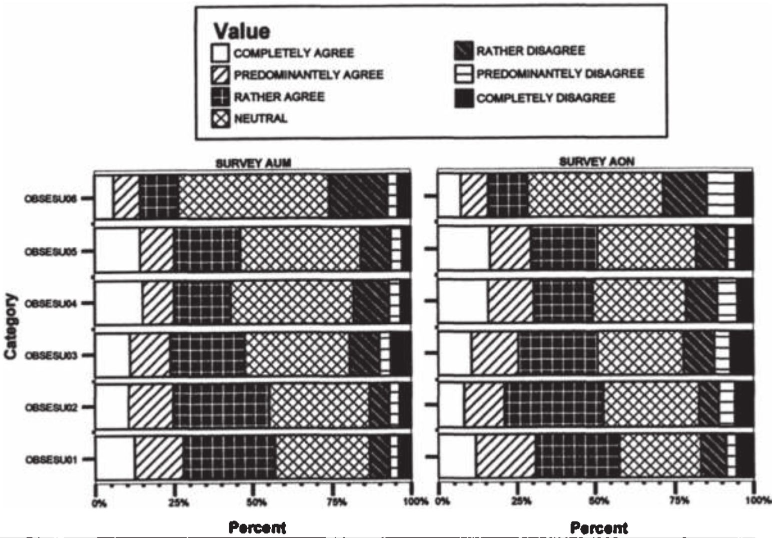
Variable Name	Statement
	Recommendations ...
BENERE01	help to reduce information overload and create a preselection for purchases.
BENERE02	help to save time.
BENERE03	keep me informed about new products and services.
BENERE04	create orientation in the mix of products and services.
BENERE05	help to find ideas for presents.
BENERE06	inform about complementary products.
BENERE07	help to find new interesting products.
BENERE08	help to avoid mispurchases.
BENERE09	call attention to low-priced products.
BENERE10	ease the navigation in online shops.

Figure 5.21: Sample description: Benefits of recommendations.

Table 5.19: Sample description: Attitudes towards implicit data collection

SURVEY AUM	OBSESU01	OBSESU02	OBSESU03	OBSESU04	OBSESU05	OBSESU06
Valid	581	581	582	578	580	577
Missing	101	101	100	104	102	105
Mean	4.73	4.67	4.47	4.56	4.61	4.10
Rank	1	2	5	4	3	6
SURVEY AON	OBSESU01	OBSESU02	OBSESU03	OBSESU04	OBSESU05	OBSESU06
Valid	306	305	302	305	303	306
Missing	90	91	94	91	93	90
Mean	4.69	4.48	4.45	4.59	4.66	4.03
Rank	1	4	5	3	2	6

In Figure 5.22 attitudes towards implicit data collection for generating recommendations are depicted. The survey participants were required to specify their degree of consent to statements regarding implicit data collection (i.e. monitoring user behavior) in online shops. Again, a seven point Likert scale ranging from totally disagree (1) to totally agree (7) is used for measurement.



Variable Name	Statement
	Implicit data collection...
OBSESU01	enables the online shop to learn my tastes and preferences without the need to input personal data.
OBSESU02	enables to continuously improve personalized recommendations.
OBSESU03	is more comfortable compared to submitting personalized data manually.
OBSESU04	is questionable from a privacy perspective.
OBSESU05	leads to losing control of how my preferences are estimated.
OBSESU06	leads to a worse estimation of my preferences and to worse recommendations compared to explicit data collection.

Figure 5.22: Sample description: Attitudes towards implicit data collection

The statements OBSESU01 to OBSESU03 highlight positive characteristics of implicit data collection, whereas statement OBSESU04 to OBSESU06 reflect critical aspects of monitoring user behavior. In Table 5.19 arithmetic means are shown. In both surveys, the participants rather agree that implicit data monitoring is a suitable method to learn preferences (OBSESU1). Interestingly, the respondents agree that using implicit methods leads to losing control with respect to the estimation of preferences (OBSESU05). However, the participants rather do not agree that this results in a lower recommendation quality (OBESU06).

Further, a bivariate correlation analysis is performed to investigate dependencies between the statements regarding implicit data collection and other factors. Table 5.20 shows statements that refer to the positive aspects of monitor-

Table 5.20: Bi–variate correlation analysis: Attitudes towards implicit data collection

Correlations Spearman's rho		AUM OBSESU1	AON OBSESU1	AUM OBSESU2	AON OBSESU2	AUM OBSESU3	AON OBSESU3
PRIVCO	Correlation Coeff.	0.01	0.05	0.00	0.01	-0.04	-0.01
	Sig. (2-tailed)	0.83	0.39	0.97	0.85	0.37	0.84
	N	576	300	576	299	577	296
EXRECO	Correlation Coeff.	0.30	0.26	0.33	0.34	0.28	0.34
	Sig. (2-tailed)	0.00	0.00	0.00	0.00	0.00	0.00
	N	578	304	578	303	579	300
TRUSSH	Correlation Coeff.	0.08	0.00	0.05	0.02	0.05	0.10
	Sig. (2-tailed)	0.05	0.94	0.21	0.76	0.25	0.08
	N	568	304	568	303	569	300
EDUCATION	Correlation Coeff.	0.01	0.05	-0.05	0.01	-0.06	0.03
	Sig. (2-tailed)	0.82	0.38	0.30	0.93	0.18	0.68
	N	483	269	483	268	484	265
AGE	Correlation Coeff.	0.00	-0.09	-0.08	-0.11	-0.03	-0.09
	Sig. (2-tailed)	0.99	0.12	0.07	0.06	0.51	0.11
	N	549	294	549	293	550	290

Correlations Spearman's rho		AUM OBSESU4	AON OBSESU4	AUM OBSESU5	AON OBSESU5	AUM OBSESU6	AON OBSESU6
PRIVCO	Correlation Coeff.	0.27	0.35	0.25	0.29	0.16	0.20
	Sig. (2-tailed)	0.00	0.00	0.00	0.00	0.00	0.00
	N	573	299	575	297	572	300
EXRECO	Correlation Coeff.	-0.12	-0.16	-0.02	-0.10	-0.08	-0.07
	Sig. (2-tailed)	0.00	0.01	0.57	0.08	0.04	0.26
	N	575	303	577	301	574	304
TRUSSH	Correlation Coeff.	-0.19	-0.26	-0.19	-0.16	-0.19	-0.16
	Sig. (2-tailed)	0.00	0.00	0.00	0.01	0.00	0.00
	N	565	303	567	301	564	304
EDUCATION	Correlation Coeff.	0.12	0.11	0.11	0.13	0.00	0.03
	Sig. (2-tailed)	0.01	0.08	0.01	0.03	0.97	0.65
	N	480	268	482	268	480	269
AGE	Correlation Coeff.	0.00	0.02	-0.01	0.04	-0.02	0.02
	Sig. (2-tailed)	0.92	0.73	0.79	0.47	0.65	0.72
	N	547	293	548	291	546	294

Table 5.21: Mann–Whitney test survey AUM: Gender–specific differences in respect to implicit data collection

Ranks	GENDER	N	Mean Rank	Sum of Ranks
OBSESU01	MALE	201	283.63	57010.50
	FEMALE	374	290.35	108589.50
	Total	575		
OBSESU02	MALE	201	283.32	56948.00
	FEMALE	374	290.51	108652.00
	Total	575		
OBSESU03	MALE	202	279.93	56545.00
	FEMALE	374	293.13	109631.00
	Total	576		
OBSESU04	MALE	201	270.69	54409.50
	FEMALE	371	295.06	109468.50
	Total	572		
OBSESU05	MALE	201	280.09	56298.00
	FEMALE	373	291.49	108727.00
	Total	574		
OBSESU06	MALE	202	281.92	56948.50
	FEMALE	370	289.00	106929.50
	Total	572		

Test Statistics	OBSESU01	OBSESU02	OBSESU03	OBSESU04	OBSESU05	OBSESU06
Mann-Whitney U	36709.50	36647.00	36042.00	34108.50	35997.00	36445.50
Wilcoxon W	57010.50	56948.00	56545.00	54409.50	56298.00	56948.50
Z	-0.48	-0.51	-0.93	-1.75	-0.81	-0.52
Asymp. Sig. (2-tailed)	0.63	0.61	0.35	0.08	0.42	0.60

ing user behavior have a significant positive relationship with the past positive experience with recommendations (EXRECO) in both surveys $\alpha = 0.05$). No

Table 5.22: Mann–Whitney test survey AON: Gender-specific differences in respect to implicit data collection

Ranks

	GENDER	N	Mean Rank	Sum of Ranks
OBSESU01	MALE	202	153.37	30980.50
	FEMALE	103	152.28	15684.50
	Total	305		
OBSESU02	MALE	201	151.39	30429.50
	FEMALE	103	154.67	15930.50
	Total	304		
OBSESU03	MALE	198	149.07	29515.00
	FEMALE	103	154.72	15936.00
	Total	301		
OBSESU04	MALE	201	155.03	31161.50
	FEMALE	103	147.56	15198.50
	Total	304		
OBSESU05	MALE	199	153.48	30543.50
	FEMALE	103	147.67	15209.50
	Total	302		
OBSESU06	MALE	202	154.04	31115.50
	FEMALE	103	150.97	15549.50
	Total	305		

Test Statistics

	OBSESU01	OBSESU02	OBSESU03	OBSESU04	OBSESU05	OBSESU06
Mann-Whitney U	10328.50	10128.50	9814.00	9842.50	9853.50	10193.50
Wilcoxon W	15684.50	30429.50	29515.00	15198.50	15209.50	15549.50
Z	-0.10	-0.32	-0.55	-0.72	-0.56	-0.30
Asymp. Sig. (2-tailed)	0.92	0.75	0.58	0.47	0.57	0.76

other significant relationships were detected. Statements that accentuate negative aspects have significant inverse relationships with privacy concerns and a positive relationship with trust in online shopping respectively. Further, people that have experienced positive recommendations in the past (EXRECO) rather reject that user monitoring is questionable from a privacy perspective (OBSESU04). People with a higher educational level are more likely to agree that user monitoring results in losing control of the estimation of preferences (OBSESU05) in both surveys. Referring to privacy issues (OBSESU04) and the educational level the situation is ambiguous. Although a significant positive relationship exists in survey AUM, in survey AON a significant relationship is not given on a significance level of 0.05 (Sig. is 0.08). As shown, the age of the respondents does neither influence statements that mention positive aspects of user monitoring nor statements that influence negative aspects. Additionally, a Mann–Whitney test shows no differences between male and female respondents regarding these statements in both surveys.

Figure 5.23 illustrates the importance of explanations for the survey respondents. Explanations expose the reasoning behind the recommendation (see Section 3.2). As shown, explanations are a fairly important issue for the respondents in both surveys. The arithmetic mean is 4.80 in survey AUM and 4.42 in survey AON respectively.

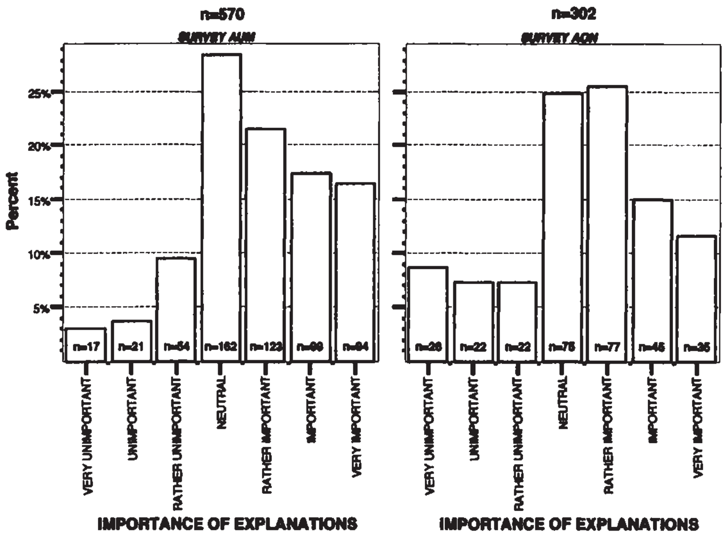


Figure 5.23: Sample description: Importance of explanations

Table 5.23: Mann–Whitney test survey AUM: Gender–specific differences regarding explanations

Ranks

	GENDER	N	Mean Rank	Sum of Ranks
FUNCEXPL	MALE	196	281.97	55267.00
	FEMALE	368	282.78	104063.00
	Total	564		

Test Statistics

	FUNCEXPL
Mann-Whitney U	35961.00
Wilcoxon W	55267.00
Z	-0.06
Asymp. Sig. (2-tailed)	0.95

Table 5.24: Mann–Whitney test survey AON: Gender–specific differences regarding explanations

Ranks

	GENDER	N	Mean Rank	Sum of Ranks
FUNCEXPL	MALE	199	150.76	30000.50
	FEMALE	102	151.48	15450.50
	Total	301		

Test Statistics

	FUNCEXPL
Mann-Whitney U	10100.50
Wilcoxon W	30000.50
Z	-0.07
Asymp. Sig. (2-tailed)	0.94

Table 5.23 and Table 5.24 depict that gender–specific differences regarding the importance of explanations (FUNCEXPL) are non existent in both surveys. Further, Table 5.25 illustrates the results of a bi–variate correlation analysis. Past positive experience with recommendations (EXRECO) and the importance of explanation are significantly positively interrelated in both surveys ($\alpha = 0.05$), i.e. respondents with a positive experience are more likely to expect explanatory capabilities from recommender systems. No relationships are detected between educational level, trust in online shopping (TRUSSH) and privacy concerns (PRIVCO). In regard to the age of respondents no univocal results are given. Whereas a significant inverse relationship is found in survey AON, in survey AUM the required significance level of 0.05 is not met (Sig. is 0.07).

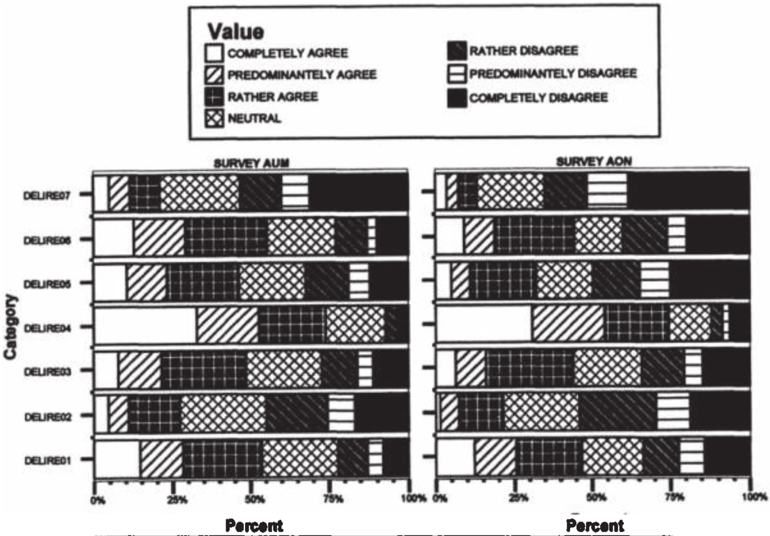
Table 5.25: Bi–variate correlation analysis: Importance of explanations

Correlations		AUM	AON
Spearman's rho		FUNCEXPL	FUNCEXPL
AGE	Correlation Coefficient	-0.08	-0.16
	Sig. (2-tailed)	0.07	0.01
	N	539	290
EDUCATION	Correlation Coefficient	-0.03	0.08
	Sig. (2-tailed)	0.54	0.19
	N	474	265
EXRECO	Correlation Coefficient	0.36	0.38
	Sig. (2-tailed)	0.00	0.00
	N	568	300
TRUSSH	Correlation Coefficient	0.04	0.01
	Sig. (2-tailed)	0.37	0.88
	N	557	300
PRIVCO	Correlation Coefficient	0.070	0.093
	Sig. (2-tailed)	0.095	0.111
	N	566	296

Table 5.26: Sample description: Delivery of recommendations

SURVEY AUM	DELIRE01	DELIRE02	DELIRE03	DELIRE04	DELIRE05	DELIRE06	DELIRE07
Valid	579	577	575	579	577	577	573
Missing	103	105	107	103	105	105	109
Mean	4.53	3.55	4.23	5.46	4.17	4.52	3.13
Rank	2	6	4	1	5	3	7
SURVEY AON	DELIRE01	DELIRE02	DELIRE03	DELIRE04	DELIRE05	DELIRE06	DELIRE07
Valid	305	302	302	303	304	303	305
Missing	91	94	94	93	92	93	91
Mean	4.14	3.27	3.97	5.33	3.38	3.87	2.70
Rank	2	6	3	1	5	4	7

Figure 5.24 refers to the delivery of online product recommendations. A seven point Likert scale ranging from totally disagree (1) to totally agree (7) is used to measure the degree of consent to specific modes of delivery. As Table 5.26 illustrates, the respondents prefer recommendations on explicit request in both surveys (DELIRE04). Furthermore, respondents rather agree to receive recommendations immediately after logging into the shop (DELIRE01).

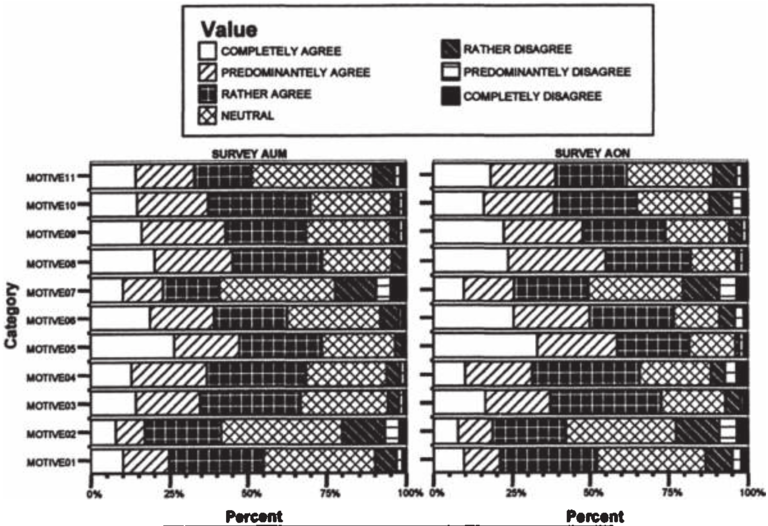


Variable Name	Statement
	I want to receive recommendations...
DELIRE01	immediately after logging into the online shop.
DELIRE02	when I browse the online shop.
DELIRE03	when I examine specific products.
DELIRE04	when I explicitly request recommendations.
DELIRE05	at regular intervals by e–mail.
DELIRE06	at certain events (e.g. new product is on the market) by e–mail.
DELIRE07	via traditional mail.

Figure 5.24: Sample description: Delivery of recommendations

The respondents rather reject to receive recommendations by traditional mail (DELIRE07) and while browsing the shop (DELIRE02).

In Figure 5.25 assigned motives for provision of recommendations are illustrated. Here, the survey participants were asked to estimate interests e–vendors pursue with the employment of online product recommendations. A seven point Likert scale ranging from totally disagree (1) to totally agree (7) was used to measure statements regarding the assumed interests of e–vendors. As Table 5.27 shows the highest degree of consent is found regarding the increase of sales (MOTIVE05) in both surveys. Further, the survey participants think that e–vendors employ recommender systems to learn consumer trends (MOTIVE08). The respondents rather disagree that e–vendors try to sell shelf–warmers (MOTIVE02) or customer data (MOTIVE07).



Variable Name	Statement
	E-vendors provide online recommendations...
MOTIVE01	to distinguish themselves from competitors.
MOTIVE02	to get rid of shelf-warmers.
MOTIVE03	to increase the loyalty of customers.
MOTIVE04	to ease shopping for customers.
MOTIVE05	to increase sales.
MOTIVE06	to collect customer data.
MOTIVE07	to sell customer data to third parties.
MOTIVE08	to recognize consumer trends.
MOTIVE09	to tailor ads towards the individual.
MOTIVE10	to improve the mix of products and services.
MOTIVE11	to sell products with a high margin.

Figure 5.25: Sample description: Assigned motives for the provision of recommendations

5.1.5 Ratings and Comments

In this section the importance of product-related reviews in form of ratings and text comments for the buying decision is discussed. In addition, motives for submitting reviews are illustrated.

Figure 5.1.5 refers to the importance of product-related ratings and text comments for the buying decision of the survey participants. The respondents were asked to answer this question on a seven point Likert scale ranging from very unimportant to very important. Sample size, missing values, arithmetic means and rank of importance for both surveys are depicted in Table 5.28. The table

Table 5.27: Sample description: Assigned motives for the provision of recommendations

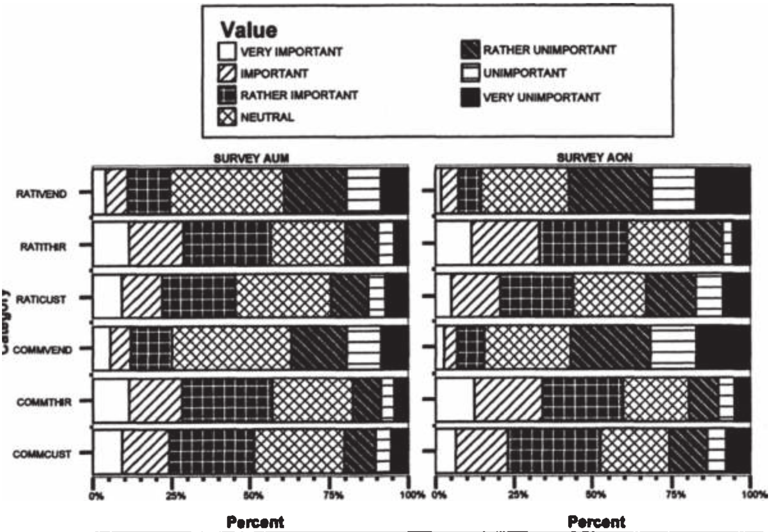
SURVEY AUM	MOTIVE01	MOTIVE02	MOTIVE03	MOTIVE04	MOTIVE05	
Valid	579	579	579	578	577	
Missing	103	103	103	104	105	
Mean	4.76	4.38	5.07	5.10	5.41	
Rank	9	10	7	5	1	
SURVEY AUM	MOTIVE06	MOTIVE07	MOTIVE08	MOTIVE09	MOTIVE10	MOTIVE11
Valid	580	579	578	579	576	577
Missing	102	103	104	103	106	105
Mean	5.08	4.36	5.32	5.19	5.15	4.83
Rank	6	11	2	3	4	8
SURVEY AON	MOTIVE01	MOTIVE02	MOTIVE03	MOTIVE04	MOTIVE05	
Valid	303	304	302	305	302	
Missing	93	92	94	91	94	
Mean	4.62	4.33	5.15	4.85	5.66	
Rank	9	11	5	8	1	
SURVEY AON	MOTIVE06	MOTIVE07	MOTIVE08	MOTIVE09	MOTIVE10	MOTIVE11
Valid	302	302	304	304	304	303
Missing	94	94	92	92	92	93
Mean	5.37	4.51	5.53	5.36	5.01	5.03
Rank	3	10	2	4	7	6

Table 5.28: Sample description: Importance of different sources of product–related reviews

SURVEY AUM	RATICUST	RATITHIR	RATIVEND	COMMCUST	COMMTHIR	COMMVEND
Valid	584	582	581	579	584	583
Missing	98	100	101	103	98	99
Mean	4.32	4.63	3.72	4.48	4.66	3.77
Rank	4	2	6	3	1	5
SURVEY AON	RATICUST	RATITHIR	RATIVEND	COMMCUST	COMMTHIR	COMMVEND
Valid	584	582	581	579	584	583
Missing	98	100	101	103	98	99
Mean	4.32	4.63	3.72	4.48	4.66	3.77
Rank	4	2	6	3	1	5

shows that the two surveys show identical results in respect of the importance of the different kinds of reviews (i.e. comments and ratings). Text comments from independent third parties (COMMTHIR) are rated as most important for the buying decision, followed by ratings from independent third parties (RATITHIR). Text comments from customers of an online shop (COMMCUST) are the 3rd most important source of product–related information, followed by ratings from other customers (RATICUST). The least important categories are text comments provided by employees of the e–vendor (COMMVEND)and ratings provided by employees of the e–vendor (RATIVEND).

A Whitney–Mann test was performed to investigate gender–specific differences in regard to the importance of the different sources of ratings and comments. As Table 5.29 and Table 5.30 show, in both studies no differences between male and female respondents were detected ($\alpha = 0.05$).



Variable Name	Source of product-related review
RATICUST	Ratings from customers of the online shop
RATITHIR	Ratings from independent third parties (e.g. consumer protection agencies, critics)
RATIVEND	Ratings from the employees of the online shop.
COMMCUST	Text comments from customers of the online shop
COMMTHIR	Text comments from independent third parties (e.g. consumer protection agencies, critics)
COMMMANU	Text comments from the manufacturer of the product
COMMVEND	Text comments from employees of the online shop

Figure 5.26: Sample description: Importance of ratings and comments for buying decisions

Table 5.31 summarizes a bi-variate correlation analysis between the different kinds of product-related reviews and past positive experience with online product recommendations (EXRECO), education and age of the respondents. As shown, a significant positive relationship between past positive experience with recommendations and the interest in all the different forms of ratings and comments exists in both surveys. In other words, the more positive experience with recommendations the respondents had in the past, the more they are interested in different forms of comments and ratings. Interestingly, the correlation coefficients illustrate that comments and ratings from other customers are the most valuable source of information for respondents that already have a positive experience with recommendations. Regarding the educational level the correlation analysis shows a significant relationship between comments and ratings from the e-vendor in both surveys. That is, the lower the educational

Table 5.29: Mann–Whitney test survey AUM: Gender–specific differences of importance of ratings and comments

Ranks

	GENDER	N	Mean Rank	Sum of Ranks
RATICUST	MALE	202	284.14	57396.00
	FEMALE	374	290.86	108780.00
	Total	576		
RATITHIR	MALE	202	294.39	59467.00
	FEMALE	372	283.76	105558.00
	Total	574		
RATIVEND	MALE	201	284.88	57260.00
	FEMALE	372	288.15	107191.00
	Total	573		
COMMCUST	MALE	200	277.47	55494.50
	FEMALE	371	290.60	107811.50
	Total	571		
COMMTHIR	MALE	202	297.01	59996.50
	FEMALE	374	283.90	106179.50
	Total	576		
COMMVEND	MALE	201	282.13	56709.00
	FEMALE	374	291.15	108891.00
	Total	575		

Test Statistics

	RATICUST	RATITHIR	RATIVEND	COMMCUST	COMMTHIR	COMMVEND
Mann-Whitney U	36893.00	36180.00	36959.00	35394.50	36054.50	36408.00
Wilcoxon W	57396.00	105558.00	57260.00	55494.50	106179.50	56709.00
Z	-0.47	-0.76	-0.23	-0.93	-0.92	-0.64
Sig. (2-tailed)	0.64	0.45	0.82	0.35	0.36	0.52

Table 5.30: Mann–Whitney test survey AON: Gender–specific differences of importance of ratings and comments

Ranks

	GENDER	N	Mean Rank	Sum of Ranks
RATICUST	MALE	202	155.44	31398.00
	FEMALE	104	149.74	15573.00
	Total	306		
RATITHIR	MALE	202	154.30	31169.50
	FEMALE	103	150.44	15495.50
	Total	305		
RATIVEND	MALE	202	156.52	31617.00
	FEMALE	102	144.54	14743.00
	Total	304		
COMMCUST	MALE	202	152.80	30866.00
	FEMALE	103	153.39	15799.00
	Total	305		
COMMTHIR	MALE	202	158.40	31996.50
	FEMALE	103	142.41	14668.50
	Total	305		
COMMVEND	MALE	201	157.56	31670.50
	FEMALE	102	141.03	14385.50
	Total	303		

Test Statistics

	RATICUST	RATITHIR	RATIVEND	COMMCUST	COMMTHIR	COMMVEND
Mann-Whitney U	10113.00	10139.50	9490.00	10363.00	9312.50	9132.50
Wilcoxon W	15573.00	15495.50	14743.00	30866.00	14668.50	14385.50
Z	-0.54	-0.37	-1.15	-0.06	-1.53	-1.59
Sig. (2-tailed)	0.59	0.71	0.25	0.96	0.13	0.11

level of the respondent the more important are comments and ratings that stem from the e–vendor to him or her. Further, a significant negative relationship between the age and the interest in comments and ratings from other customers exits in both surveys, i.e. the younger the respondents the more likely they are interested in comments and ratings from other customers.

Table 5.31: Bi–variate correlation analysis: Importance of comments and ratings from customers, independent third parties and e–vendors

Correlations Spearman's rho		AUM COMMCUST	AON COMMCUST	AUM RATICUST	AON RATICUST
EXRECO	Correlation Coefficient	0.54	0.55	0.52	0.52
	Sig. (2-tailed)	0.00	0.00	0.00	0.00
	N	576	305	581	307
EDUCATION	Correlation Coefficient	0.00	-0.03	-0.06	-0.10
	Sig. (2-tailed)	0.96	0.60	0.19	0.09
	N	480	270	485	270
RESPOAGE	Correlation Coefficient	-0.19	-0.23	-0.19	-0.19
	Sig. (2-tailed)	0.00	0.00	0.00	0.00
	N	545	294	550	295
		AUM COMMTHIR	AON COMMTHIR	AUM RATITHIR	AON RATITHIR
EXRECO	Correlation Coefficient	0.39	0.32	0.35	0.24
	Sig. (2-tailed)	0.00	0.00	0.00	0.00
	N	581	304	579	305
EDUCATION	Correlation Coefficient	0.12	0.05	0.07	0.06
	Sig. (2-tailed)	0.01	0.42	0.11	0.32
	N	485	270	483	270
RESPOAGE	Correlation Coefficient	-0.03	-0.07	-0.03	-0.01
	Sig. (2-tailed)	0.55	0.22	0.54	0.80
	N	550	294	548	294
		AUM COMMVEND	AON COMMVEND	AUM RATIVEND	AON RATIVEND
EXRECO	Correlation Coefficient	0.38	0.44	0.37	0.46
	Sig. (2-tailed)	0.00	0.00	0.00	0.00
	N	580	303	578	304
EDUCATION	Correlation Coefficient	-0.16	-0.18	-0.16	-0.20
	Sig. (2-tailed)	0.00	0.00	0.00	0.00
	N	484	269	482	269
RESPOAGE	Correlation Coefficient	-0.08	-0.05	-0.07	-0.06
	Sig. (2-tailed)	0.06	0.43	0.10	0.30
	N	549	292	547	293

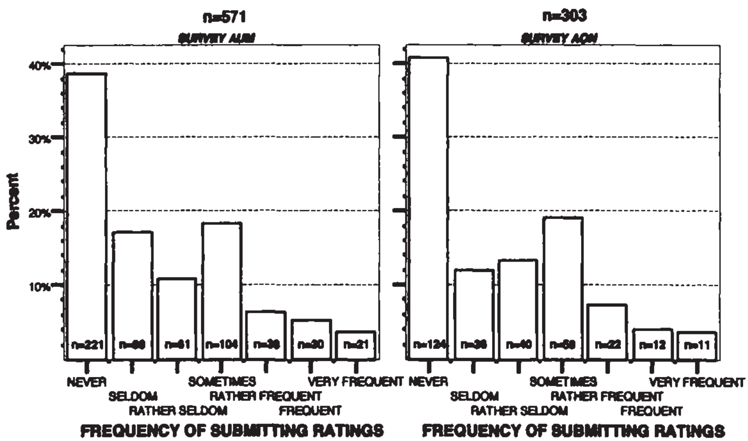


Figure 5.27: Sample description: Frequency of submitting product–related ratings

In Figure 5.27 the frequency of submitting product–related ratings to online shops is illustrated. The results of the two surveys look fairly similar. The majority in both surveys (38.7% in survey AUM and 40.9% in survey AON) have never submitted a product–related rating to an online store. The arithmetic mean of survey AUM is 2.67 and 2.66 in survey AON respectively.

In respect to the submission of product–related text comments to online shops the frequency of doing this is even lower. As Figure 5.28 shows, in survey AUM 46% of the respondents have never provided comments. In survey AON, 45.9% have never submitted this kind of information to an online shop. The arithmetic mean accounts for 2.30 in survey AON and 2.34 in survey AUM respectively.

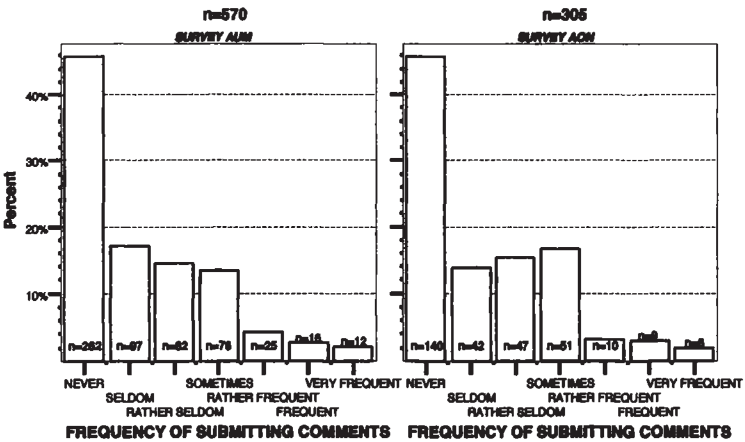


Figure 5.28: Sample description: Frequency of submitting product–related text comments

To determine gender specific differences in respect to the submission frequency of ratings and comments two Mann–Whitney tests were performed. As Table 5.32 and Table 5.33 indicate, significant differences where found in both surveys($\alpha = 0.05$). In both surveys male respondents submit ratings (FREQRATI) as well as comments (FREQCOMM) more often than female respondents.

Table 5.32: Mann–Whitney test survey AUM: Gender–specific differences in respect to the submission of ratings and comments

Ranks

	GENDER	N	Mean Rank	Sum of Ranks
FREQRATI	MALE	194	303.79	58934.50
	FEMALE	369	270.55	99831.50
	Total	563		
FREQCOMM	MALE	194	301.77	58543.00
	FEMALE	368	270.82	99660.00
	Total	562		

Test Statistics

	FREQRATI	FREQCOMM
Mann-Whitney U	31566.50	31764.00
Wilcoxon W	99831.50	99660.00
Z	-2.39	-2.27
Asymp. Sig. (2-tailed)	0.02	0.02

Table 5.33: Mann–Whitney test survey AON: Gender–specific differences in respect to the submission of ratings and comments

Ranks

	GENDER	N	Mean Rank	Sum of Ranks
FREQRATI	MALE	198	158.54	31391.50
	FEMALE	102	134.89	13758.50
	Total	300		
FREQCOMM	MALE	199	158.95	31631.00
	FEMALE	103	137.11	14122.00
	Total	302		

Test Statistics

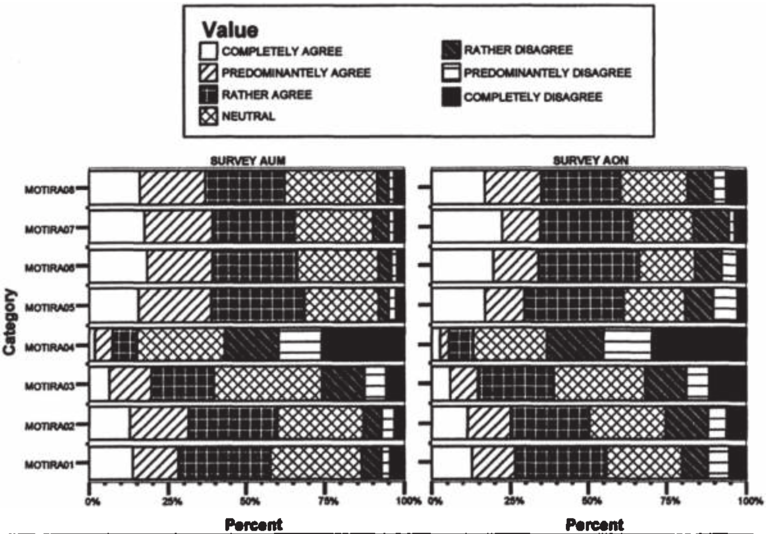
	FREQRATI	FREQCOMM
Mann-Whitney U	8505.50	8766.00
Wilcoxon W	13758.50	14122.00
Z	-2.33	-2.18
Asymp. Sig. (2-tailed)	0.02	0.03

The correlation analysis in Table 5.34 shows interrelationships of the frequency of submitting ratings and comments with other factors ($\alpha = 0.05$). As shown a significant inverse relationship exists between the frequency of providing ratings as well as comments and the age of the respondents (RESPOAGE) in both surveys. Hence, younger people seem to provide ratings and comments more often. No significant relationships were found between the educational level and the frequency of submission. Furthermore, privacy concerns (PRIVCO) show no significant influence on the submission frequency. Previous positive experience with recommendations (EXRECO) and shopping (EXSHOP) as well as the time spent on the Internet (INTEHOUR) have a significant positive relationship to the submission frequency.

Figure 5.29 refers to motives for submitting product–related reviews of survey participants that have already submitted reviews. The survey participants where asked to specify the degree of consent of statements regarding motives for submitting reviews. A seven point Likert scale ranging from totally disagree

Table 5.34: Bi–variate correlation analysis: Frequency of submitting product–related ratings and comments

Correlations Spearman's rho		AUM FREQRATI	AON FREQRATI	AUM FREQCOMM	AON FREQCOMM
RESPOAGE	Correlation Coefficient	-0.21	-0.21	-0.15	-0.16
	Sig. (2-tailed)	0.00	0.00	0.00	0.01
	N	537	290	536	292
EDUCATION	Correlation Coefficient	-0.04	-0.08	-0.07	-0.08
	Sig. (2-tailed)	0.35	0.20	0.10	0.21
	N	475	265	475	266
EXRECO	Correlation Coefficient	0.36	0.45	0.36	0.43
	Sig. (2-tailed)	0.00	0.00	0.00	0.00
	N	569	302	568	304
EXSHOP	Correlation Coefficient	0.28	0.29	0.29	0.24
	Sig. (2-tailed)	0.00	0.00	0.00	0.00
	N	569	302	568	304
PRIVCO	Correlation Coefficient	-0.029	-0.009	-0.050	0.018
	Sig. (2-tailed)	0.484	0.882	0.234	0.760
	N	567	297	566	299
INTEHOUR	Correlation Coefficient	0.22	0.18	0.18	0.14
	Sig. (2-tailed)	0.00	0.00	0.00	0.02
	N	555	289	554	291



Variable Name	Statement
	I submit product–related reviews...
MOTIRA01	to alleviate the buying decision of other consumers.
MOTIRA02	if I receive incentives from the e–vendor.
MOTIRA03	to communicate my tastes and preferences to get better personalized recommendations.
MOTIRA04	to get a better reputation within the virtual community of the e–vendor.
MOTIRA05	to communicate a positive experience with the product.
MOTIRA06	to communicate a negative experience with the product.
MOTIRA07	to prevent other consumers from having a bad experience with the product.
MOTIRA08	to promote a product I like.

Figure 5.29: Sample description: Motives for submitting reviews.

Table 5.35: Sample description: Motives for submitting reviews

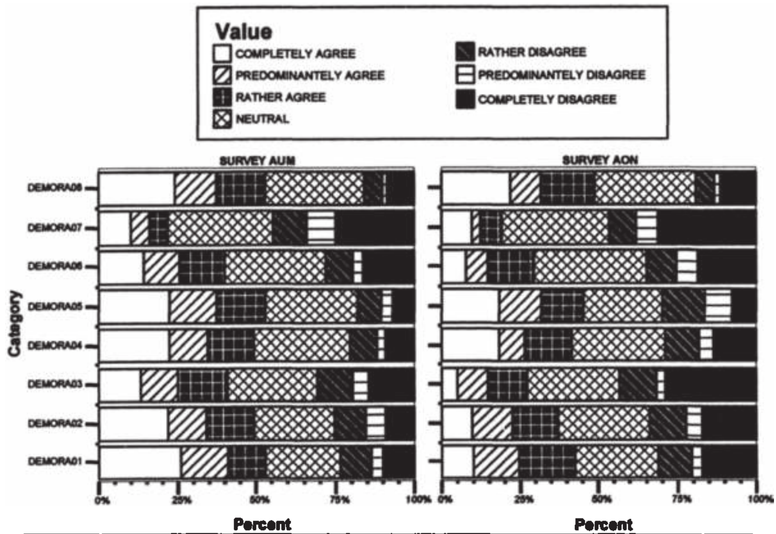
SURVEY AUM				
	MOTIRA01	MOTIRA02	MOTIRA03	MOTIRA04
Valid	362	360	361	361
Mean	4.75	4.81	4.21	3.01
Rank	6	5	7	8
	MOTIRA05	MOTIRA06	MOTIRA07	MOTIRA08
Valid	361	360	362	360
Mean	5.07	5.09	5.04	4.99
Rank	2	1	3	4
SURVEY AON				
	MOTIRA01	MOTIRA02	MOTIRA03	MOTIRA04
Valid	183	184	184	184
Mean	4.57	4.43	3.97	2.83
Rank	5	6	7	8
	MOTIRA05	MOTIRA06	MOTIRA07	MOTIRA08
Valid	183	184	183	183
Mean	4.75	4.93	4.96	4.77
Rank	4	2	1	3

(1) to totally agree (7) was used to measure the degree of acceptance of the respondents. Table 5.35 compares the arithmetic means of the motives for submitting reviews. The higher the arithmetic means the higher is the degree of consent of the survey participants. The results clearly show that getting a better reputation within the virtual community is not a very important motive for the survey participants. To communicate personal tastes and preferences in order to get better personalized recommendations also is not that important for the participants. In contrast, communicating either positive or negative experiences with products is an important motive in both surveys.

Table 5.36: Sample description: Motives for not submitting reviews

SURVEY AUM				
	DEMORA01	DEMORA02	DEMORA03	DEMORA04
Valid	205	205	204	204
Mean	4.73	4.56	4.14	4.65
Rank	3	5	7	4
	DEMORA05	DEMORA06	DEMORA07	DEMORA08
Valid	204	204	202	204
Mean	4.77	4.16	3.45	4.80
Rank	2	6	8	1
SURVEY AON				
	DEMORA01	DEMORA02	DEMORA03	DEMORA04
Valid	118	118	117	117
Mean	4.08	3.96	3.43	4.26
Rank	4	5	7	3
	DEMORA05	DEMORA06	DEMORA07	DEMORA08
Valid	117	118	116	116
Mean	4.41	3.73	3.25	4.59
Rank	2	6	8	1

In Figure 5.30 and Table 5.36 motives that prevent survey participants from providing ratings and comments are shown. The results refer to participants that have never submitted a rating or comment. The results suggest that having little experience with the product is a very important factor for not



Variable Name	Statement
	I do not submit product-related reviews...
DEMORA01	because writing a text comment is too time-consuming.
DEMORA02	because providing a rating is too time-consuming.
DEMORA03	because incentives from the e-vendor are not given.
DEMORA04	because I do not expect any benefit from doing that.
DEMORA05	because in general I have no interest in reviews.
DEMORA06	because I have reservations in respect to privacy issues.
DEMORA07	because I have never bought in an online shop that supports reviews from customers.
DEMORA08	if my experience with the product is low.

Figure 5.30: Sample description: Motives for not submitting reviews

submitting reviews. The impression that reviews offer no benefit to the individual is also an important factor for not submitting reviews in both surveys. Further, text comments are perceived as relative time–consuming amongst the respondents.

5.2 Verification of the Research Model

In the following sections, the hypotheses and the research model presented in Chapter 4 are verified. A factor analysis, a structural equation model that tests the psychographic hypotheses, and regression models that verify further psychographic and sociodemographic hypotheses are examined.

5.2.1 Exploratory Factor Analysis

This section deals with the results of the exploratory factor analysis. This analysis is performed to check the validity of the measurement scales in the first survey (AUM). Although a confirmative factor analysis is inherently performed in the context of the structural equation model, the exploratory factor analysis is made for the following three reasons:

1. to shorten the questionnaire in the second survey. Measurement scales are reduced to the three highest loading factors. Those reduced scales are used in the follow–up survey conducted in cooperation with AON.

2. to check for adulteration due to the translation– and retranslation–process of measurement scales taken from literature prior to the model estimation.

3. to check the validity of the scales developed by the author prior to the model estimation.

As mentioned above in survey AUM, the sample size accounts for 682. 606 cases show no missing values in respect to the variables used in the research model. About 20% (i.e.130) of these cases are randomly chosen (using SPSS 12.0.1) to perform the factor analysis and are removed from the dataset on which the structural equation model is calculated to avoid fitting the "model to the data". As a consequence 476 cases remained for the calculation of the structural equation model.

In accordance with recent literature regarding factor analysis [Rus02, CO05, CH03, Pet00] principal axis factoring was used as the factor extraction procedure. Promax with Kaiser normalization was employed used as factor rotation method. Factors with Eigenvalues greater than 1 were extracted.

Kaiser–Meyer–Olkin measure of sampling adequacy (MSA) accounts for 0.768. According to this criterion the data is well–suited to perform an exploratory factor analysis. An MSA-Value ≥ 0.7 indicates a "pretty good" appropriateness of the data for an exploratory factor analysis [BEPW03].

Table 5.37: Factor analysis AUM: Pattern matrix

Pattern Matrix Factor	1	2	3	4	5	6	7	8	9
CIMISP01				0.84					
CIMISP02				0.55					
CIMISP03				0.73					
CIMISP04				0.93					
CISYMB01							0.83		
CISYMB02							0.86		
CISYMB03							0.89		
CIHEDO01			0.96						
CIHEDO02			0.90						
CIHEDO03			0.95						
OPLEAD01									0.71
OPLEAD02									0.65
OPLEAD03									0.69
OPLEAD04						0.80			
OPLEAD05						0.89			
OPLEAD06						0.86			
OPSEEK01					0.84				
OPSEEK02					0.09				
OPSEEK03					0.63				
OPSEEK04					0.74				
OPSEEK05					0.83				
OPSEEK06					0.51				
INREAD01		0.86							
INREAD02		0.79							
INREAD03		0.97							
INREAD04		0.80							
INWRIT01								0.68	
INWRIT02								0.94	
INWRIT03								0.77	
INWRIT04								0.58	
INRECO01	0.75								
INRECO02	0.95								
INRECO03	0.95								
INRECO04	0.74								

In Table 5.37 the loadings of the exploratory factor analysis are shown. CIMISP refers to the "subjective probability of making a mispurchase" facet of the consumer involvement profiles scale by Laurent and Kapferer [KL86]. CISYMB denotes the "symbolic sign or value attributed by the consumer to the product class" facet of the consumer involvement profiles scale [KL86]. CIHEDO marks the "hedonic value of the product class" according to the consumer involvement profiles scale [KL86]. OPLEAD and OPSEEK indicate the opinion leadership and opinion seeking items as proposed by Flynn, Goldsmith, and Eastman [FGE96]. INREAD, INWRIT, and INRECO are scales designed by the author. INREAD measures the "interest in reading evaluations of books from other customers of an online shop". INWRIT denotes the "interest in writing evaluations of books in an online shop". Finally, INRECO refers to the "interest in obtaining personalized book–recommendations in an online shop".

As depicted in the Table 5.37, the opinion leadership measurement scale loads on two independent factors instead of one as expected. As a consequence, nine factors are extracted (using Eigenvalues greater than 1 as a criterion for factor extraction) instead of eight (as eight measurement scales are employed). The author assumes that this is due to cultural differences and/or the product class (i.e. books). The scale was originally developed and tested with American students. Table 5.38 shows the items of that scale. OPLEAD01 to OPLEAD03 are reverse scaled whereas OPLEAD04 to OPLEAD06 are normally scaled. Probably, OPLEAD01 to OPLEAD03 loads on a different factor, because social desirableness may play an important role in the context of books and due to the negative formulation of the questions. The author has decided to employ OPLEAD04 to OPLEAD06 for the estimation of the model, as factor loadings are generally higher and social desirableness might not play such an important role due to the wording of the questions.

Table 5.38: Opinion leaders by Flynn, Goldsmith, and Eastman

OPLEAD01	My opinion on books seems not to count with other people.
OPLEAD02	When they choose books, other people do no turn to me for advice.
OPLEAD03	Other people rarely come to me for advice about choosing books.
OPLEAD04	People that I know pick books based on what I have told them.
OPLEAD05	I often persuade others to buy the books that I like.
OPLEAD06	I often influence people's opinions about books.

Table 5.39: Reliability and validity of the scales used for the model estimation

Multi-Item Measure	Cronbach's Alpha	Items	Factor Loading
Consumer Involvement Risk of Mispurchase	0.861	CIMISP01	0.84
		CIMISP03	0.73
		CIMISP04	0.93
Consumer Involvement Symbolic Sign	0.891	CISYMB01	0.83
		CISYMB02	0.86
		CISYMB03	0.89
Consumer Involvement Hedonic Value	0.947	CIHEDO01	0.96
		CIHEDO02	0.90
		CIHEDO03	0.96
Opinion Leading	0.878	OPLEAD04	0.80
		OPLEAD05	0.89
		OPLEAD06	0.86
Opinion Seeking	0.868	OPSEEK01	0.84
		OPSEEK04	0.74
		OPSEEK05	0.83
Interest in Reading	0.907	INREAD01	0.86
		INREAD03	0.97
		INREAD04	0.80
Interest in Writing	0.894	INWRIT01	0.68
		INWRIT02	0.94
		INWRIT03	0.77
Interest in Recommendations	0.911	INRECO01	0.75
		INRECO02	0.95
		INRECO03	0.95

Table 5.39 illustrates the scales and corresponding items that are used in the structural equation models described in Section 5.2.2. Cronbach's Alpha is depicted to indicate the reliability of the multi–item measures. Values between 0.8 and 0.9 indicate a "moderate to high level reliability" [DeV96]. Values

above 0.9 signify a "high level" of reliability [DeV96]. As shown, all the scales used for the model fall into this two categories.

5.2.2 Psychographic Hypotheses – Structural Equation Model

In this section, the research model in respect of the psychographic factors is verified. The programm AMOS 5.0 is used for the calculation of the model. Maximum likelihood (ML) is used as method for the estimation of the model parameters. Maximum likelihood is the most widespread estimation method in international marketing research [HB95b]. This method requires the manifest (i.e. observed) variables to have a multivariate normal distribution. In the context of marketing research, it is very common that the data will fail the assumption of normality. This is also the case in both surveys conducted in the context of this survey. This is assessed by taking a look at Mardia's coefficient and its critical value. In survey AUM Mardia's coefficient accounts for 274.272 and exceeds its critical value of 84.693 by far. Thus, normality of the data can not be assumed. This is also the case in survey AON, where Mardia's coefficient is 169.168 and the critical ratio would be 44.472.

As normality is not given in both surveys the following two options are possible to estimate the model: (1) to use an estimation method that does not require a multivariate normal distribution (e.g. unweighed least squares) or (2) to perform bootstrapping in conjunction with the maximum likelihood estimation method. As maximum likelihood delivers more conservative estimations [AG88] the author has chosen to stick to the maximum likelihood method and to use bootstrapping.

The model consists of 61 variables. 24 variables are observed (i.e. manifest) variables and 37 are unobserved (i.e. latent) variables. 32 of the variables are exogenous and 29 are endogenous. In survey AUM, the number of cases is 476. In this survey, originally 606 cases with no missing values regarding the observed variables in the model occurred. However, 130 cases were randomly chosen for the exploratory factor analysis and were not used for the calculation of the model (see Section 5.2.1). In the follow up survey (AON), the number of cases with no missing values in respect of the observed variables accounts for 345.

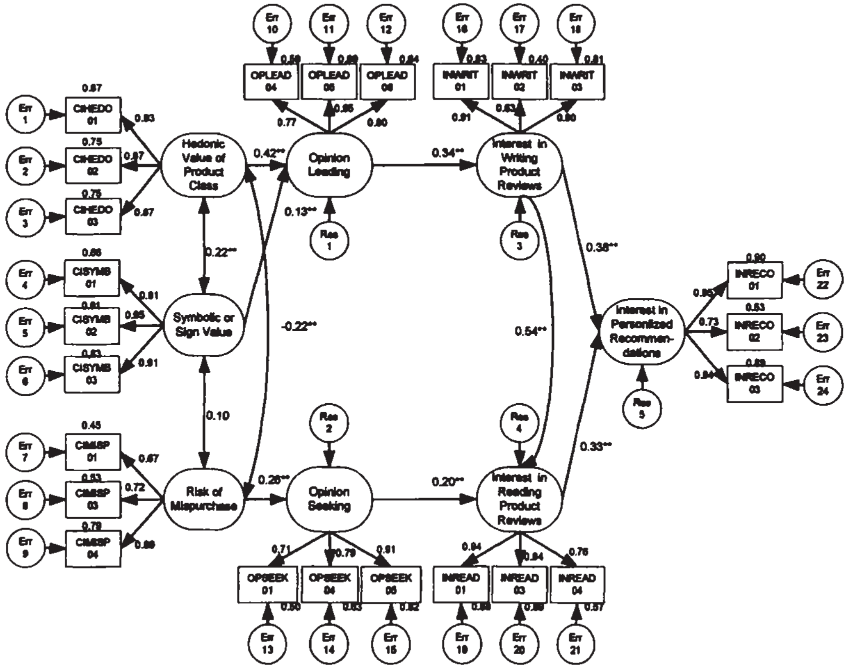


Figure 5.31: Structural equation model: Survey AUM

Figure 5.31 shows the results of the model tested on the dataset of survey AUM. As shown, all regression paths are significant on a level of 0.01. The covariance of the symbolic sign or value and the risk of a mispurchase is not significant.

Figure 5.32 depicts the results of the model with the data from survey AON. Again all regression paths are significant on a significance level of 0.01. The covariance of the hedonic value of the product class and the risk of a mispurchase is not significant.

The research hypothesis regarding the structural equation model are summarized in Table 5.40. In both surveys, the hypothesis regarding the model are

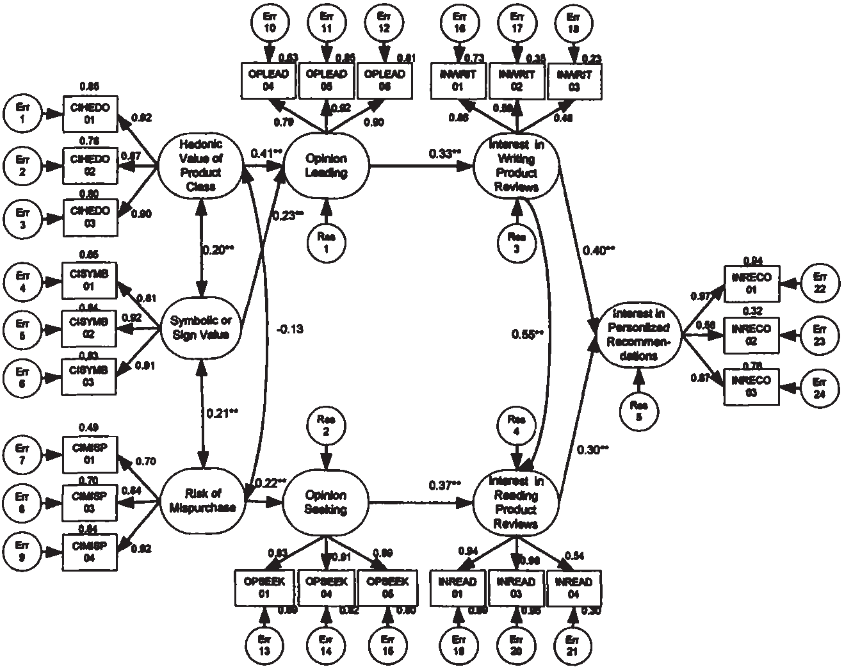


Figure 5.32: Structural equation model: Survey AON

of high significance ($\alpha = 0.01$). The regression weights are shown to indicate the strength of the influence.

In Table 5.41, the fit indices of the model are depicted. According to the literature, different levels of threshold are depicted for both the GFI and AGFI indices. According to Sharma [Sha96] an AGFI above 0.8 indicates a good model fit. Other researchers (e.g. [HB95a, HATB98]) set the threshold for the AGFI to 0.9. However, both threshold values have no statistical basis. They are derived from practical experience. In literature different fit–indices, their explanatory power and thresholds are lively discussed. For instance, Hu and Bentler generally advise against using the GFI and AGFI as fit indicators [HB99]. In respect to the IFI, TLI, and CFI the established threshold of 0.9 is met. According to Browne and Cudeck a RMSEA below 0.05 indicates a good model fit and a RSMEA below 0.08 indicates a reasonable model

Table 5.40: Summarization of model–specific research hypotheses

No.	Hypothesis	AUM Std. Reg.	AUM Sig.	AON Std. Reg.	AON Sig.
H1	The higher consumers assess the hedonic value of books, the more likely they tend to engage in opinion leading.	0.42	$p< 0.01$	0.41	$p< 0.01$
H2	The higher consumers assess the symbolic sign or value of books, the more likely they engage in opinion leading.	0.13	$p< 0.01$	0.23	$p< 0.01$
H3	The higher consumers assess the risk of making a mispurchase, the more likely they engage in opinion seeking.	0.22	$p< 0.01$	0.22	$p< 0.01$
H4	The more consumers engage in opinion leading, the more likely they are interested in writing book–related reviews in virtual communities of e–vendors.	0.34	$p< 0.01$	0.33	$p< 0.01$
H5	The more consumers engage in opinion seeking, the more likely they are interested in reading book–related reviews in virtual communities of e–vendors.	0.20	$p< 0.01$	0.37	$p< 0.01$
H6	The more consumers are interested in writing book–related reviews, the more they are interested in reading reviews of other consumers.	0.54	$p< 0.01$	0.55	$p< 0.01$
H7	The more consumers take part in the virtual community of the e–vendor, the more they are interested in personalized recommendations.				
H7a	The more consumers are interested in writing book–related reviews, the more they are interested in personalized book recommendations.	0.38	$p< 0.01$	0.40	$p< 0.01$
H7b	The more consumers are interested in reading book–related reviews, the more they are interested in personalized book recommendations.	0.33	$p< 0.01$	0.30	$p< 0.01$

fit [BC93]. The second threshold level is met in both surveys. Hence, the author assumes an adequate model–fit in both surveys.

Table 5.41: Fit–indices of the research model

Fit Measure	Model AUM	Model AON
GFI	0.878	0.847
AGFI	0.848	0.810
IFI (Incremental Fit Index)	0.939	0.923
TLI (Tucker–Lewis Index)	0.930	0.912
CFI (Comparative Fit Index)	0.939	0.923
RMSEA	0.066	0.074

5.2.3 Psychographic Hypotheses - Regression Model

In the following, further psychographic determinations of the interest in personalized book recommendations are investigated. These factors include scepticism towards advertising (SKEPAD) [OS98], impulse buying tendency (IMPUBU) [WJB97], domain–specific innovativeness (DOINNO) [GH91], privacy concerns (PRIVCO), and experience with online shopping (EXSHOP). A regression model was chosen, because including these scales in the structural equation model would lead to a overly complex model.

The measurements where tested in respect to reliability (Cronbach's alpha) and validity (factor analysis with principal axis factoring and promax rotation). As shown in Table 5.42, the scales are well–suited for a regression analysis in terms of reliability and validity.

Table 5.42: Reliability and validity of the scales used for the regression model

Scale	Cronbach's Alpha (AUM)	Cronbach's Alpha (AON)	Item	Factor Loading (AUM)	Factor Loading (AON)
Impulse Buying Tendency	0.829	0.882	IMPUBU01	0.72	0.78
			IMPUBU03	0.88	0.93
			IMPUBU04	0.76	0.83
Privacy Concerns	0.948	0.947	PRIVCO01	0.92	0.90
			PRIVCO02	0.95	0.94
			PRIVCO03	0.91	0.92
Skepticism towards Advertising	0.885	0.880	SKEPAD03	0.88	0.87
			SKEPAD04	0.83	0.85
			SKEPAD05	0.85	0.83
Domain–Specific Innovativeness	0.819	0.899	DOINNO01	0.94	0.91
			DOINNO02	0.78	0.90
			DOINNO06	0.61	0.81
Experience with Online Shopping	0.873	0.868	EXSHOP01	0.82	0.92
			EXSHOP03	0.83	0.75
			EXSHOP04	0.86	0.80
Interest in personalized Book Recommendations	0.904	0.837	INRECO01	0.95	0.94
			INRECO02	0.79	0.63
			INRECO03	0.93	0.89

Table 5.43: Verification of hypotheses survey AUM: Psychographic factors that influence interest in book recommendations

INRECO					
R	R Square	Adjusted R Square	Std. Error of the Estimate		
0.30	0.09	0.08	1.54		
ANOVA					
	Sum of Squares	df	Mean Square	F	Sig.
Regression	149.81	5	29.96	12.61	0.00
Residual	1556.40	655	2.38		
Total	1706.21	660			
COEFFICIENTS					
	B	Std. Error	Beta	t	Sig.
(Constant)	2.10	0.42		5.04	0.00
IMPUBU	-0.01	0.04	-0.01	-0.19	0.85
PRIVCO	0.06	0.04	0.05	1.31	0.19
EXSHOP	0.26	0.04	0.25	6.19	0.00
SKEPAD	-0.04	0.05	-0.03	-0.84	0.40
DOINNO	0.17	0.05	0.15	3.85	0.00

In Table 5.43 and Table 5.44, the results of the regression model are set out. In both surveys, experience with online shopping and domain specific innovativeness significantly influence the interest in personalized online book recommen-

Table 5.44: Verification of hypotheses survey AON: Psychographic factors that influence interest in book recommendations

INRECO					
R	R Square	Adjusted R Square	Std. Error of the Estimate		
0.25	0.06	0.05	1.49		
ANOVA					
	Sum of Squares	df	Mean Square	F	Sig.
Regression	52.62	5	10.52	4.71	0.00
Residual	813.38	364	2.23		
Total	866.00	369			
COEFFICIENTS					
	B	Std. Error	Beta	t	Sig.
(Constant)	2.83	0.49		5.81	0.00
IMPUBU	0.08	0.05	0.09	1.73	0.08
PRIVCO	-0.01	0.06	-0.01	-0.11	0.92
EXSHOP	0.14	0.05	0.14	2.51	0.01
SKEPAD	-0.05	0.06	-0.05	-0.89	0.37
DOINNO	0.14	0.06	0.13	2.49	0.01

dations ($\alpha = 0.05$). According to this results, the hypothesis are summarized in Table 5.45.

Table 5.45: Summarization of the psychographic hypotheses

No.	Hypothesis	AUM Std. Reg.	AUM Sig.	AON Std. Reg.	AON Sig.
H8	The higher the impulse buying tendency of a person, the higher the interest in personalized book–recommendations.	-0.01	N.S.	0.09	N.S.
H9	The higher the privacy concerns of a person, the lower is the interest in personalized book–recommendations.	0.05	N.S.	-0.01	N.S.
H10	The higher the online shopping experience of a person, the higher the interest in personalized book–recommendations.	0.25	p<0.01	0.14	p<0.05
H11	The higher the skepticism towards advertising of a person, the lower is the interest in personalized book–recommendations.	-0.03	N.S.	-0.05	N.S.
H12	The higher the domain specific innovativeness of a person, the higher is the interest in personalized book–recommendations.	0.15	p<0.01	0.13	p<0.05

5.2.4 Sociodemographic Hypotheses

This section deals with the verification of the hypotheses that include sociodemographic factors. The question is, whether sociodemographic factors have a significant influence on: (1) the interest in personalized recommendations, (2) the interest in writing book–related reviews, (3) the interest in reading book–related reviews of other consumers.

As shown in Table 5.46, no differences between men and woman are found

Table 5.46: Verification of hypotheses: Gender–specific differences

Ranks						
AUM	GENDER	N	Mean Rank	Sum of Ranks		
INRECO	MALE	200	269.00	53800.50		
	FEMALE	375	298.13	111799.50		
	Total	575				
INWRIT	MALE	201	284.17	57117.50		
	FEMALE	374	290.06	108482.50		
	Total	575				
INREAD	MALE	198	273.27	54107.00		
	FEMALE	373	292.76	109199.00		
	Total	571				
AON	GENDER	N	Mean Rank	Sum of Ranks		
INRECO	MALE	202	148.26	29948.50		
	FEMALE	103	162.30	16716.50		
	Total	305				
INWRIT	MALE	201	154.64	31083.00		
	FEMALE	103	148.32	15277.00		
	Total	304				
INREAD	MALE	203	148.15	30074.00		
	FEMALE	103	164.05	16897.00		
	Total	306				
Test Statistics						
	AUM INRECO	AON INRECO	AUM INWRIT	AON INWRIT	AUM INREAD	AON INREAD
Mann-Whitney U	33700.50	9445.50	36816.50	9921.00	34406.00	9368.00
Wilcoxon W	53800.50	29948.50	57117.50	15277.00	54107.00	30074.00
Z	-2.01	-1.32	-0.41	-0.60	-1.35	-1.49
Asymp. Sig. (2-tailed)	0.04	0.19	0.68	0.55	0.18	0.14

in both surveys regarding the interest in writing and reading product–related reviews. In survey AON, a gender-specific difference regarding interest in recommendations is found on a significance level of 0.05 but not on a level of 0.01. In survey AUM, a significant difference between male and female respondents is not detected.

Table 5.47 and Table 5.48 investigate, whether educational level and age of the respondents have an influence in regard to the interest in personalized recommendations, in writing book–related reviews, and in reading book–related reviews. As shown, the educational level of the respondents has no significant influence on these three factors. In the contrary, the age of the respondents has a significant influence on the three factors ($\alpha = 0.05$).

The demographic research hypotheses are summarized in Table 5.49. Besides the standardized regression coefficients the significance level is depicted. "N.S." indicates that on a level of 0.05 the hypothesis is not significant.

Table 5.47: Verification of hypotheses survey AUM: Differences due to age and education

INRECO		Adjusted	Std. Error of		
R	R Square	R Square	the Estimate		
0.16	0.03	0.02	1.62		
ANOVA					
	Sum of Squares	df	Mean Square	F	Sig.
Regression	31.12	2	15.56	5.95	0.00
Residual	1200.48	459	2.62		
Total	1231.59	461			
COEFFICIENTS					
	B	Std. Error	Beta	t	Sig.
(Constant)	5.00	0.32		15.69	0.00
EDUCATION	-0.04	0.08	-0.02	-0.42	0.67
RESPOAGE	-0.02	0.01	-0.16	-3.39	0.00
INWRIT		Adjusted	Std. Error of		
R	R Square	R Square	the Estimate		
0.14	0.02	0.01	1.56		
ANOVA					
	Sum of Squares	df	Mean Square	F	Sig.
Regression	20.86	2	10.43	4.29	0.01
Residual	1117.02	459	2.43		
Total	1137.87	461			
COEFFICIENTS					
	B	Std. Error	Beta	t	Sig.
(Constant)	4.26	0.31		13.90	0.00
EDUCATION	-0.08	0.08	-0.05	-0.98	0.33
RESPOAGE	-0.02	0.01	-0.12	-2.68	0.01
INREAD		Adjusted	Std. Error of		
R	R Square	R Square	the Estimate		
0.12	0.01	0.01	1.64		
ANOVA					
	Sum of Squares	df	Mean Square	F	Sig.
Regression	17.17	2	8.59	3.19	0.04
Residual	1223.08	455	2.69		
Total	1240.25	457			
COEFFICIENTS					
	B	Std. Error	Beta	t	Sig.
(Constant)	4.76	0.32		14.78	0.00
EDUCATION	0.12	0.08	0.07	1.40	0.16
RESPOAGE	-0.01	0.01	-0.10	-2.19	0.03

Table 5.48: Verification of hypotheses survey AON: Differences due to age and education

INRECO		Adjusted	Std. Error of		
R	R Square	R Square	the Estimate		
0.16	0.03	0.02	1.52		
ANOVA					
	Sum of		Mean		
	Squares	df	Square	F	Sig.
Regression	15.82	2	7.91	3.40	0.03
Residual	592.63	255	2.32		
Total	608.44	257			
COEFFICIENTS					
	B	Std. Error	Beta	t	Sig.
(Constant)	4.71	0.39		12.18	0.00
EDUCATION	-0.02	0.11	-0.01	-0.20	0.84
RESPOAGE	-0.02	0.01	-0.16	-2.56	0.01
INWRIT		Adjusted	Std. Error of		
R	R Square	R Square	the Estimate		
0.17	0.03	0.02	1.54		
ANOVA					
	Sum of		Mean		
	Squares	df	Square	F	Sig.
Regression	17.92	2	8.96	3.78	0.02
Residual	601.89	254	2.37		
Total	619.81	256			
COEFFICIENTS					
	B	Std. Error	Beta	t	Sig.
(Constant)	4.67	0.39		11.94	0.00
EDUCATION	-0.14	0.11	-0.08	-1.26	0.21
RESPOAGE	-0.02	0.01	-0.14	-2.29	0.02
INREAD		Adjusted	Std. Error of		
R	R Square	R Square	the Estimate		
0.24	0.06	0.05	1.57		
ANOVA					
	Sum of		Mean		
	Squares	df	Square	F	Sig.
Regression	37.38	2	18.69	7.55	0.00
Residual	634.13	256	2.48		
Total	671.51	258			
COEFFICIENTS					
	B	Std. Error	Beta	t	Sig.
(Constant)	4.99	0.40		12.50	0.00
EDUCATION	0.15	0.11	0.08	1.34	0.18
RESPOAGE	-0.03	0.01	-0.23	-3.77	0.00

Table 5.49: Summarization of the demographic hypotheses

No.	Hypothesis	AUM Std. Reg.	AUM Sig.	AON Std. Reg.	AON Sig.
H13	Gender influences the interest in personalized recommendations.	N.A.	p<0.05	N.A.	N.S.
H14	Gender influences the interest in writing book-related reviews.	N.A.	N.S.	N.A.	N.S.
H15	Gender influences the interest in reading book-related reviews of other consumers.	N.A.	N.S.	N.A.	N.S.
H16	The older persons are, the lower is their interest in personalized book-recommendations.	-0.16	p<0.01	-0.16	p<0.05
H17	The older persons are, the lower is their interest in writing book-related reviews.	-0.12	p<0.05	-0.14	p<0.05
H18	The older persons are, the lower is their interest reading book-related reviews of other consumers.	-0.10	p<0.05	-0.23	p<0.01
H19	The higher the educational level of persons, the higher is their interest in personalized book-recommendations.	-0.02	N.S.	-0.01	N.S.
H20	The higher the educational level of persons, the higher is their interest in writing book-related reviews.	-0.05	N.S.	-0.08	N.S.
H21	The higher the educational level of persons, the higher is their interest in reading book-related reviews.	0.07	N.S.	0.08	N.S.

Chapter 6

Summary and Directions for Further Research

The research goal was to examine the underlying psychographic and sociodemographic determinants that influence: (1) the consumer's interest in *personalized recommendations*, (2) the consumer's interest in participating actively in virtual communities of transaction located at online purchase environments by *submitting product–related ratings and comments*, and (3) the consumer's interest in *product–related opinions of other consumers* in virtual communities. This research question was addressed in the context of books that are sold over electronic purchase environments. In the following, the main findings and implications as well as limitations and directions for further research are set out.

6.1 Main Findings

In the course of the book, two surveys were conducted. The first survey was made in cooperation with the Austrian bookseller A&M Andreas & Dr. Müller Verlagsbuchhandel (www.aum.at). In this survey the sample size accounts for 682 persons. The second survey was conducted in cooperation with the Internet service provider Telekom Austria AG (www.aon.at). In total 396 respondents filled out the questionnaire of the second survey. The software packages SPSS 12.0.1 and AMOS 5.0 were used for the data analysis.

The main results of the surveys are:

- The opinion leadership model (i.e. involvement leads to opinion leadership and opinion leadership has a positive influence on word–of–mouth) is also applicable for electronic purchase environments. More specifically, online purchasers with a high involvement in respect of the hedonic value and the symbolic sign of books tend to engage in opinion leading. Opinion leading itself results in word–of–mouth by submitting product–related reviews in virtual communities of transactions. Further, the surveys show that involvement regarding the risk of a mispurchase results in opinion seeking.

- Interest in word–of–mouth (i.e. reading and submitting product–related reviews in virtual communities) is coupled to interest in personalized recommendations provided by recommender systems in online purchase environments.

- Domain specific innovativeness is an important psychographic factor that influences the interest in personalized recommendations.

- According to the surveys, privacy concerns of consumers do not affect negatively the interest in personalized recommendations.

- An interrelation between the impulse buying tendency of a consumer and the interest in recommendations was not found in the surveys.

- The consumer's scepticism towards advertising does not seem to influence negatively the interest in recommendations.

- There are no gender–specific differences regarding the interest in recommendations.

- The older consumers are the lower is their interest in recommendations.

- Consumers with experience regarding recommender systems and a high impulse buying tendency tend to buy recommended books immediately in the e–vendor's online purchase environment given that they are interested in the recommended books.

- Male consumers tend to submit product–related reviews more often than female consumers. Furthermore, younger persons tend to provide reviews more often.

6.2 Limitations and Directions for Further Research

This work is subject to a variety of (partly inevitable) limitations. Firstly, the surveys were posted in German language on web–sited mainly visited by Austrian consumers. Hence, the results may not be representative for consumers that stem from other countries or regions. A cross–cultural study would be an interesting point of contact for further research.

Further, using a web–based questionnaire leads to the problem of self–selection of the survey participants. Self–selection refers to the fact that the researcher is not in control of the selection process of the survey participants (e.g. by selecting participants randomly). For instance, consumers with a high interest in the topic may be overrepresented in the sample.

The surveys were limited to a specific type of products. Books were used to test the model. However, the question remains, if the model is still valid with other product classes. For instance, if products are chosen that can be described using "objective criteria" (e.g. personal computers, digital photo cameras) it is questionable, whether opinion leaders are still interested in word–of–mouth from other consumers and recommendations respectively. Hence, it would be interesting to test the model on other product classes.

The model does not investigate if the interest in recommendations leads to a change in the (buying) behavior of consumers. As the theory of reasoned action (TRA) suggests that a change in the attitude (e.g. the interest in recommendations) is reflected by a change in behavior [AF80], it would be of interest to include behavioral aspects (e.g. adoption of recommendations) in the model. The technology acceptance model (TAM) [Dav89], which is based on the theory of reasoned action and includes behavioral aspects, should be a promising approach for further research on recommender systems.

The author believes that he has made a relevant contribution to the research regarding online product recommendations. In respect of the growing importance of the field, this work hopefully encourages others to examine further factors that are of relevance for recommendation purposes.

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Appendix A

AMOS Output

A.1 Survey AUM

Analysis Summary

Date and Time

Date: Dienstag, 11. April 2006
Time: 12:26:22

Title

model_aum_bootstrapped: Dienstag, 11. April 2006 12:26

Groups

Group number 1 (Group number 1)

Notes for Group (Group number 1)

The model is recursive.
Sample size = 476

Variable Summary (Group number 1)

Your model contains the following variables (Group number 1)

Observed, endogenous variables
CIHEDO03
CIHEDO02
CIHEDO01
CISYMB03
CISYMB02
CISYMB01
OPLEAD04
OPLEAD05
OPLEAD06
INWRIT01
INWRIT02
INWRIT03
INRECO01
INRECO02
INRECO03
INREAD01
INREAD03
INREAD04
OPSEEK01

OPSEEK04
OPSEEK05
CIMISP04
CIMISP03
CIMISP01
Unobserved, endogenous variables
OPLEAD
INWRIT
INRECO
INREAD
OPSEEK
Unobserved, exogenous variables
CIHEDO
Err3
Err2
Err1
CISYMB
Err6
Err5
Err4
Err10
Err11
Err12
Res1
Err16
Err17
Err18
Res3
Err22
Err23
Err24
Res5
Err19
Err20
Err21
Res4
Err13
Err14
Err15
CIMISP
Err9
Err8
Err7
Res2

Variable counts (Group number 1)

Number of variables in your model:	61
Number of observed variables:	24
Number of unobserved variables:	37
Number of exogenous variables:	32
Number of endogenous variables:	29

Parameter summary (Group number 1)

	Weights	Covariances	Variances	Means	Intercepts	Total
Fixed	36	0	1	0	0	37
Labeled	0	0	0	0	0	0
Unlabeled	25	3	31	0	0	59
Total	61	3	32	0	0	96

Assessment of normality (Group number 1)

Variable	min	max	skew	c.r.	kurtosis	c.r.
CIMISP01	1	7	-0,127	-1,127	-0,467	-2,078
CIMISP03	1	7	0,23	2,052	-0,66	-2,941
CIMISP04	1	7	0,06	0,536	-0,431	-1,92
OPSEEK05	1	7	0,223	1,982	-0,705	-3,14
OPSEEK04	1	7	-0,115	-1,023	-0,569	-2,535
OPSEEK01	1	7	0,226	2,013	-0,601	-2,678
INREAD04	1	7	-0,269	-2,392	-0,72	-3,208
INREAD03	1	7	-0,449	-4	-0,631	-2,81
INREAD01	1	7	-0,445	-3,962	-0,56	-2,495
INRECO03	1	7	-0,131	-1,169	-0,723	-3,22

INRECO02	1	7	-0,188	-1,677	-0,7	-3,117
INRECO01	1	7	-0,157	-1,398	-0,761	-3,39
INWRIT03	1	7	0,237	2,11	-0,671	-2,989
INWRIT02	1	7	0,17	1,514	-0,891	-3,969
INWRIT01	1	7	0,306	2,725	-0,589	-2,625
OPLEAD06	1	7	-0,203	-1,807	-0,601	-2,677
OPLEAD05	1	7	-0,234	-2,084	-0,533	-2,375
OPLEAD04	1	7	-0,239	-2,131	-0,16	-0,712
CISYMB01	1	7	-0,402	-3,58	-0,057	-0,256
CISYMB02	1	7	-0,424	-3,78	-0,232	-1,031
CISYMB03	1	7	-0,484	-4,309	-0,095	-0,423
CIHEDO01	1	7	-0,882	-7,854	0,429	1,908
CIHEDO02	1	7	-0,938	-8,354	0,73	3,251
CIHEDO03	1	7	-1,249	-11,123	1,46	6,501
Multivariate					274,272	84,693

Observations farthest from the centroid (Mahalanobis distance) (Group number 1)

Observation number	Mahalanobis d-squared	p1	p2
82	121,027	0	0
350	117,041	0	0
303	103,874	0	0
394	102,643	0	0
312	101,35	0	0
16	95,882	0	0
257	93,013	0	0
300	87,781	0	0
309	81,328	0	0
157	79,857	0	0
197	78,519	0	0
396	75,571	0	0
281	73,848	0	0
151	73,753	0	0
119	69,601	0	0
443	69,405	0	0
134	67,504	0	0
275	62,787	0	0
113	62,451	0	0
93	60,525	0	0
18	60,511	0	0
17	58,77	0	0
71	58,424	0	0
1	58,115	0	0
258	56,555	0	0
144	55,416	0	0
319	54,85	0	0
387	54,739	0	0
248	54,582	0	0
253	53,982	0	0
199	53,061	0,001	0
215	52,989	0,001	0
372	52,447	0,001	0
361	52,324	0,001	0
459	52,134	0,001	0
34	48,945	0,002	0
183	48,883	0,002	0
415	48,293	0,002	0
128	47,401	0,003	0
273	47,042	0,003	0
432	46,814	0,004	0
321	46,102	0,004	0
97	45,601	0,005	0
26	45,481	0,005	0
70	45,446	0,005	0
288	45,313	0,005	0
178	45,091	0,006	0
61	44,862	0,006	0
125	44,234	0,007	0
205	43,904	0,008	0
92	43,872	0,008	0
21	43,826	0,008	0
448	43,491	0,009	0
100	43,411	0,009	0
402	42,928	0,01	0
380	42,775	0,011	0
426	42,08	0,013	0
118	41,634	0,014	0
278	41,572	0,014	0
266	41,141	0,016	0

209	40,71	0,018	0
201	40,478	0,019	0
363	40,196	0,02	0
44	40,087	0,021	0
335	40,043	0,021	0
219	40,034	0,021	0
175	39,924	0,022	0
183	39,914	0,022	0
110	39,831	0,022	0
218	39,569	0,024	0
254	39,146	0,026	0
133	38,163	0,033	0
202	38,008	0,035	0
367	37,681	0,037	0
187	37,584	0,038	0
221	36,926	0,045	0
225	36,796	0,046	0
293	36,744	0,046	0
138	36,638	0,048	0
283	36,602	0,048	0
308	36,528	0,049	0
445	36,469	0,049	0
224	36,407	0,05	0
29	36,319	0,051	0
425	36,294	0,051	0
12	36,257	0,052	0
223	36,182	0,053	0
462	36,148	0,053	0
54	36,028	0,055	0
272	35,912	0,056	0
302	35,797	0,057	0
159	35,6	0,06	0
47	35,579	0,06	0
386	35,57	0,06	0
51	35,559	0,061	0
6	34,798	0,071	0
148	34,705	0,073	0
146	34,533	0,076	0
171	33,886	0,087	0
65	33,83	0,088	0

Models

Default model (Default model)

Notes for Model (Default model)

Computation of degrees of freedom (Default model)

Number of distinct sample moments:	300
Number of distinct parameters to be estimated:	59
Degrees of freedom (300 - 59):	241

Result (Default model)

Minimum was achieved
Chi-square = 734,150
Degrees of freedom = 241
Probability level = ,000

Group number 1 (Group number 1 - Default model)

Estimates (Group number 1 - Default model)

Scalar Estimates (Group number 1 - Default model)

Maximum Likelihood Estimates

Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
OPLEAD	<—	CIHEDO	0,349	0,041	8,499	***	
OPLEAD	<—	CISYMB	0,115	0,042	2,747	0,006	
OPLEAD	<—	Res1	0,946	0,05	18,749	***	
INWRIT	<—	OPLEAD	0,477	0,07	6,84	***	
OPSEEK	<—	CIMISP	0,286	0,06	4,748	***	

INREAD	<—	OPSEEK	0,296	0,063	4,683	***
INREAD	<—	INWRIT	0,583	0,048	12,176	***
INRECO	<—	INWRIT	0,426	0,055	7,714	***
INRECO	<—	INREAD	0,345	0,05	6,925	***
CIHEDO03	<—	CIHEDO	0,854	0,031	27,493	***
CIHEDO02	<—	CIHEDO	0,954	0,035	27,501	***
CIHEDO01	<—	CIHEDO	1			
CISYMB03	<—	CISYMB	1,112	0,046	24,243	***
CISYMB02	<—	CISYMB	1,229	0,049	25,087	***
CISYMB01	<—	CISYMB	1			
OPLEAD04	<—	OPLEAD	1			
OPLEAD05	<—	OPLEAD	1,38	0,069	20,083	***
OPLEAD06	<—	OPLEAD	1,133	0,062	18,254	***
INWRIT01	<—	INWRIT	1			
INWRIT02	<—	INWRIT	0,757	0,049	15,464	***
INWRIT03	<—	INWRIT	0,985	0,039	25,157	***
INRECO01	<—	INRECO	1			
INRECO02	<—	INRECO	0,769	0,037	20,9	***
INRECO03	<—	INRECO	0,972	0,027	36,14	***
INREAD01	<—	INREAD	1			
INREAD03	<—	INREAD	1,02	0,029	34,942	***
INREAD04	<—	INREAD	0,824	0,037	22,151	***
OPSEEK01	<—	OPSEEK	1			
OPSEEK04	<—	OPSEEK	1,122	0,071	15,733	***
OPSEEK05	<—	OPSEEK	1,323	0,083	16,01	***
CIMISP04	<—	CIMISP	1,304	0,096	13,612	***
CIMISP03	<—	CIMISP	1,115	0,083	13,43	***
CIMISP01	<—	CIMISP	1			

Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
OPLEAD	<—	CIHEDO	0,423
OPLEAD	<—	CISYMB	0,127
OPLEAD	<—	Res1	0,884
INWRIT	<—	OPLEAD	0,34
OPSEEK	<—	CIMISP	0,261
INREAD	<—	OPSEEK	0,205
INREAD	<—	INWRIT	0,541
INRECO	<—	INWRIT	0,382
INRECO	<—	INREAD	0,334
CIHEDO03	<—	CIHEDO	0,866
CIHEDO02	<—	CIHEDO	0,866
CIHEDO01	<—	CIHEDO	0,932
CISYMB03	<—	CISYMB	0,91
CISYMB02	<—	CISYMB	0,952
CISYMB01	<—	CISYMB	0,809
OPLEAD04	<—	OPLEAD	0,766
OPLEAD05	<—	OPLEAD	0,945
OPLEAD06	<—	OPLEAD	0,797
INWRIT01	<—	INWRIT	0,909
INWRIT02	<—	INWRIT	0,633
INWRIT03	<—	INWRIT	0,901
INRECO01	<—	INRECO	0,951
INRECO02	<—	INRECO	0,729
INRECO03	<—	INRECO	0,943
INREAD01	<—	INREAD	0,937
INREAD03	<—	INREAD	0,945
INREAD04	<—	INREAD	0,758
OPSEEK01	<—	OPSEEK	0,708
OPSEEK04	<—	OPSEEK	0,792
OPSEEK05	<—	OPSEEK	0,908
CIMISP04	<—	CIMISP	0,89
CIMISP03	<—	CIMISP	0,725
CIMISP01	<—	CIMISP	0,673

Covariances: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
CIHEDO	<->	CISYMB	0,332	0,078	4,258	***	
CIHEDO	<->	CIMISP	-0,332	0,073	-4,559	***	
CISYMB	<->	CIMISP	0,122	0,063	1,952	0,051	

Correlations: (Group number 1 - Default model)

			Estimate
CIHEDO	<->	CISYMB	0,216
CIHEDO	<->	CIMISP	-0,25
CISYMB	<->	CIMISP	0,101

Variances: (Group number 1 - Default model)

	Estimate	S.E.	C.R.	P	Label
Res1	1				
CIHEDO	1,687	0,129	13,033	***	
CISYMB	1,4	0,133	10,526	***	
CIMISP	1,04	0,137	7,576	***	
Res3	1,991	0,166	11,984	***	
Res2	1,166	0,141	8,273	***	
Res4	1,747	0,14	12,444	***	
Res5	1,691	0,132	12,795	***	
Err3	0,41	0,036	11,227	***	
Err2	0,51	0,045	11,221	***	
Err1	0,257	0,037	6,842	***	
Err6	0,36	0,041	8,824	***	
Err5	0,217	0,043	5,022	***	
Err4	0,737	0,055	13,372	***	
Err10	0,807	0,063	12,758	***	
Err11	0,261	0,066	3,931	***	
Err12	0,845	0,071	11,929	***	
Err16	0,471	0,069	6,839	***	
Err17	1,937	0,134	14,409	***	
Err18	0,507	0,068	7,41	***	
Err22	0,297	0,053	5,648	***	
Err23	1,456	0,101	14,473	***	
Err24	0,328	0,051	6,437	***	
Err19	0,362	0,052	6,997	***	
Err20	0,327	0,052	6,241	***	
Err21	1,317	0,093	14,182	***	
Err13	1,246	0,097	12,832	***	
Err14	0,937	0,09	10,415	***	
Err15	0,466	0,096	4,846	***	
Err9	0,463	0,099	4,692	***	
Err8	1,167	0,103	11,292	***	
Err7	1,254	0,1	12,574	***	

Squared Multiple Correlations: (Group number 1 - Default model)

	Estimate
OPLEAD	0,218
OPSEEK	0,068
INWRIT	0,116
INREAD	0,333
INRECO	0,395
CIMISP01	0,454
CIMISP03	0,526
CIMISP04	0,792
OPSEEK05	0,825
OPSEEK04	0,627
OPSEEK01	0,501
INREAD04	0,575
INREAD03	0,893
INREAD01	0,879
INRECO03	0,869
INRECO02	0,531
INRECO01	0,904
INWRIT03	0,812
INWRIT02	0,4
INWRIT01	0,827
OPLEAD06	0,635
OPLEAD05	0,893
OPLEAD04	0,587
CISYMB01	0,655
CISYMB02	0,907
CISYMB03	0,828
CIHEDO01	0,868
CIHEDO02	0,75
CIHEDO03	0,75

Modification Indices (Group number 1 - Default model)

Covariances: (Group number 1 - Default model)

			M.I.	Par Change
Res2	<->	Res1	37,626	0,347
Res2	<->	CISYMB	14,61	0,24
Res3	<->	Res2	22,119	0,374
Res4	<->	CIHEDO	6,328	0,208
Err7	<->	CISYMB	7,885	-0,182
Err8	<->	CISYMB	13,483	0,235
Err8	<->	CIHEDO	9,133	-0,209

Err8	<->	Res2	5,421	0,146
Err15	<->	CISYMB	7,262	0,149
Err15	<->	Err8	5,095	0,125
Err14	<->	CIMISP	5,281	-0,121
Err14	<->	CIHEDO	12,786	0,227
Err14	<->	Err8	7,626	-0,161
Err13	<->	Res1	11,234	0,194
Err13	<->	Err8	6,628	0,166
Err21	<->	CIMISP	14,783	-0,224
Err21	<->	Err9	5,047	-0,125
Err21	<->	Err14	4,657	0,126
Err20	<->	Res5	12,48	-0,171
Err19	<->	Res5	8,335	0,14
Err19	<->	Err7	6,91	-0,111
Err23	<->	CIMISP	26,235	-0,311
Err23	<->	Res1	11,631	-0,206
Err23	<->	Err8	4,318	-0,14
Err23	<->	Err21	87,147	0,634
Err23	<->	Err20	6,765	-0,114
Err22	<->	CIMISP	6,635	0,094
Err22	<->	Res1	4,293	0,075
Err22	<->	Res4	5,642	-0,115
Err22	<->	Err8	4,227	0,083
Err22	<->	Err21	28,793	-0,219
Err22	<->	Err19	12,473	0,093
Err18	<->	Err20	4,977	0,071
Err18	<->	Err24	9,051	0,092
Err18	<->	Err23	7,707	-0,142
Err17	<->	CIMISP	21,645	-0,328
Err17	<->	Res1	4,577	-0,149
Err17	<->	Err9	9,154	-0,203
Err17	<->	Err21	50,642	0,558
Err17	<->	Err23	57,548	0,62
Err17	<->	Err22	8,961	-0,147
Err16	<->	Err21	8,944	-0,147
Err16	<->	Err24	12,004	-0,105
Err16	<->	Err22	11,764	0,105
Err12	<->	CISYMB	4,309	0,111
Err12	<->	Err13	4,634	0,116
Err12	<->	Err19	7,868	0,098
Err11	<->	Res2	4,654	0,099
Err11	<->	Err20	6,543	0,076
Err10	<->	Res4	5,442	-0,144
Err10	<->	Err7	5,39	0,121
Err10	<->	Err8	9,943	-0,163
Err10	<->	Err16	5,351	0,091
Err4	<->	Err23	5,255	0,119
Err4	<->	Err18	4,217	-0,077
Err5	<->	Err8	5,363	0,088
Err5	<->	Err15	7,602	0,09
Err5	<->	Err18	6,12	0,071
Err5	<->	Err16	5,929	-0,07
Err5	<->	Err12	18,959	0,138
Err5	<->	Err11	4,561	-0,059
Err6	<->	Res3	6,25	0,12
Err6	<->	Err12	10,677	-0,104
Err1	<->	Err7	4,434	0,08
Err1	<->	Err8	9,519	-0,116
Err1	<->	Err18	6,537	0,074
Err2	<->	Res1	5,104	0,089
Err2	<->	CISYMB	5,744	0,105
Err2	<->	Err18	5,678	-0,079
Err3	<->	Res1	8,001	-0,099
Err3	<->	Res2	5,227	-0,088
Err3	<->	Res3	10,853	-0,163
Err3	<->	Err13	4,81	-0,086
Err3	<->	Err17	4,892	0,105

Variances: (Group number 1 - Default model)

			M.I.	Par Change

Regression Weights: (Group number 1 - Default model)

			M.I.	Par Change
OPSEEK	<—	Res1	37,626	0,347
OPSEEK	<—	CISYMB	16,897	0,189
OPSEEK	<—	OPLEAD	42,946	0,34
OPSEEK	<—	INWRIT	43,783	0,246

INWRIT	<—	OPSEEK	23,639	0,317
INREAD	<—	CIHEDO	6,867	0,135
CIMISP01	<—	CISYMB	6,462	-0,121
CIMISP01	<—	INREAD01	4,843	-0,07
CIMISP01	<—	INRECO02	5,586	-0,073
CIMISP01	<—	CISYMB01	4,08	-0,076
CIMISP01	<—	CISYMB02	7,456	-0,098
CIMISP01	<—	CISYMB03	4,074	-0,076
CIMISP03	<—	CISYMB	8,922	0,141
CIMISP03	<—	CIHEDO	4,268	-0,089
CIMISP03	<—	OPSEEK	4,967	0,115
CIMISP03	<—	OPSEEK05	6,418	0,084
CIMISP03	<—	OPSEEK01	10,174	0,109
CIMISP03	<—	CISYMB01	6,027	0,091
CIMISP03	<—	CISYMB02	10,453	0,115
CIMISP03	<—	CISYMB03	5,553	0,088
CIMISP03	<—	CIHEDO01	7,12	-0,104
CIMISP04	<—	INWRIT02	8,187	-0,074
OPSEEK05	<—	CISYMB	5,996	0,1
OPSEEK05	<—	CIMISP03	6,333	0,075
OPSEEK05	<—	CISYMB01	4,747	0,07
OPSEEK05	<—	CISYMB02	7,979	0,087
OPSEEK04	<—	CIMISP	11,126	-0,175
OPSEEK04	<—	CIHEDO	19,273	0,174
OPSEEK04	<—	OPLEAD	11,934	0,167
OPSEEK04	<—	INWRIT	7,859	0,097
OPSEEK04	<—	INREAD	5,44	0,074
OPSEEK04	<—	INRECO	6,407	0,077
OPSEEK04	<—	CIMISP01	4,258	-0,068
OPSEEK04	<—	CIMISP03	15,834	-0,126
OPSEEK04	<—	CIMISP04	7,26	-0,089
OPSEEK04	<—	INREAD04	9,456	0,087
OPSEEK04	<—	INREAD01	4,902	0,064
OPSEEK04	<—	INRECO03	4,145	0,059
OPSEEK04	<—	INRECO02	8,153	0,08
OPSEEK04	<—	INRECO01	6,482	0,072
OPSEEK04	<—	INWRIT03	7,889	0,085
OPSEEK04	<—	INWRIT02	7,655	0,076
OPSEEK04	<—	OPLEAD05	10,948	0,105
OPSEEK04	<—	OPLEAD04	12,384	0,125
OPSEEK04	<—	CIHEDO01	17,572	0,149
OPSEEK04	<—	CIHEDO02	11,527	0,118
OPSEEK04	<—	CIHEDO03	18,011	0,164
OPSEEK01	<—	Res1	11,234	0,194
OPSEEK01	<—	CIHEDO	4,076	-0,088
OPSEEK01	<—	CIMISP03	8,174	0,099
OPSEEK01	<—	INRECO03	4,424	0,067
OPSEEK01	<—	OPLEAD06	7,361	0,097
OPSEEK01	<—	CIHEDO03	7,051	-0,113
INREAD04	<—	CIMISP	13,006	-0,209
INREAD04	<—	OPLEAD	4,909	-0,118
INREAD04	<—	CIMISP01	4,142	-0,073
INREAD04	<—	CIMISP03	9,586	-0,108
INREAD04	<—	CIMISP04	13,347	-0,134
INREAD04	<—	INRECO02	39,805	0,196
INREAD04	<—	INWRIT02	19,289	0,134
INREAD04	<—	INWRIT01	5,421	-0,077
INREAD04	<—	OPLEAD06	5,002	-0,08
INREAD04	<—	OPLEAD05	4,331	-0,073
INREAD04	<—	CISYMB03	4,062	-0,076
INREAD03	<—	INRECO	6,62	-0,056
INREAD03	<—	CIMISP01	4,165	0,048
INREAD03	<—	INRECO03	4,165	-0,042
INREAD03	<—	INRECO02	12,661	-0,071
INREAD03	<—	INRECO01	7,999	-0,057
INREAD01	<—	CIHEDO	4,325	0,059
INREAD01	<—	INRECO	5,746	0,052
INREAD01	<—	INRECO01	9,135	0,061
INREAD01	<—	OPLEAD06	6,381	0,059
INREAD01	<—	CIHEDO01	4,474	0,054
INREAD01	<—	CIHEDO02	5,662	0,059
INRECO02	<—	CIMISP	25,857	-0,307
INRECO02	<—	Res1	11,631	-0,206
INRECO02	<—	OPLEAD	10,867	-0,183
INRECO02	<—	OPSEEK	4,167	-0,111
INRECO02	<—	CIMISP01	18,603	-0,162
INRECO02	<—	CIMISP03	22,284	-0,172
INRECO02	<—	CIMISP04	20,139	-0,171
INRECO02	<—	OPSEEK05	4,257	-0,072
INRECO02	<—	OPSEEK01	5,207	-0,082
INRECO02	<—	INREAD04	39,3	0,203

INRECO02	<—	INWRIT02 28,029	0,168
INRECO02	<—	OPLEAD06 9,403	-0,115
INRECO02	<—	OPLEAD05 10,208	-0,117
INRECO02	<—	OPLEAD04 8,213	-0,117
INRECO02	<—	CISYMB03 4,03	-0,079
INRECO01	<—	CIMISP 6,715	0,094
INRECO01	<—	Res1 4,293	0,075
INRECO01	<—	OPLEAD 4,813	0,073
INRECO01	<—	OPSEEK 4,981	0,073
INRECO01	<—	CIMISP03 9,211	0,066
INRECO01	<—	CIMISP04 4,73	0,05
INRECO01	<—	OPSEEK05 4,225	0,043
INRECO01	<—	OPSEEK04 4,59	0,046
INRECO01	<—	INREAD04 17,252	-0,081
INRECO01	<—	OPLEAD06 5,093	0,051
INRECO01	<—	OPLEAD04 6,516	0,063
INWRIT03	<—	OPSEEK 4,332	0,082
INWRIT03	<—	CIMISP03 4,255	0,054
INWRIT03	<—	OPSEEK04 4,743	0,057
INWRIT02	<—	CIMISP 21,732	-0,325
INWRIT02	<—	Res1 4,577	-0,149
INWRIT02	<—	OPLEAD 4,568	-0,137
INWRIT02	<—	CIMISP01 12,087	-0,151
INWRIT02	<—	CIMISP03 9,804	-0,131
INWRIT02	<—	CIMISP04 22,653	-0,21
INWRIT02	<—	INREAD04 24,857	0,186
INWRIT02	<—	INRECO02 32,383	0,212
INWRIT02	<—	OPLEAD06 7,101	-0,115
INWRIT02	<—	OPLEAD04 6,561	-0,121
INWRIT01	<—	OPLEAD04 5,633	0,07
OPLEAD06	<—	CIMISP 4,672	0,104
OPLEAD06	<—	CISYMB 4,026	0,079
OPLEAD06	<—	OPSEEK 4,186	0,088
OPLEAD06	<—	CIMISP03 6,864	0,076
OPLEAD06	<—	OPSEEK05 4,004	0,056
OPLEAD06	<—	OPSEEK01 7,776	0,08
OPLEAD06	<—	CISYMB02 7,608	0,081
OPLEAD05	<—	OPSEEK 4,542	0,08
OPLEAD05	<—	OPSEEK05 4,183	0,05
OPLEAD05	<—	OPSEEK04 4,302	0,052
OPLEAD04	<—	CIMISP 5,23	-0,106
OPLEAD04	<—	INREAD 5,377	-0,064
OPLEAD04	<—	CIMISP03 12,414	-0,098
OPLEAD04	<—	INREAD03 6,037	-0,062
OPLEAD04	<—	INREAD01 4,558	-0,054
OPLEAD04	<—	CIHEDO02 4,51	0,065
CISYMB02	<—	OPLEAD04 4,275	-0,047
CISYMB03	<—	INWRIT 7,656	0,062
CISYMB03	<—	INREAD 5,036	0,046
CISYMB03	<—	INRECO 5,972	0,048
CISYMB03	<—	INREAD03 4,368	0,039
CISYMB03	<—	INREAD01 4,909	0,041
CISYMB03	<—	INRECO03 6,164	0,047
CISYMB03	<—	INRECO01 5,169	0,042
CISYMB03	<—	INWRIT03 4,266	0,041
CISYMB03	<—	INWRIT01 8,793	0,058
CISYMB03	<—	CIHEDO02 4,234	0,046
CIHEDO01	<—	CIMISP01 4,232	0,043
CIHEDO01	<—	INWRIT03 6,226	0,049
CIHEDO02	<—	Res1 5,104	0,089
CIHEDO02	<—	CISYMB 4,952	0,072
CIHEDO02	<—	OPLEAD 5,049	0,081
CIHEDO02	<—	INRECO 5,526	0,053
CIHEDO02	<—	INREAD01 4,659	0,046
CIHEDO02	<—	INRECO03 5,242	0,049
CIHEDO02	<—	INRECO01 5,274	0,048
CIHEDO02	<—	OPLEAD05 4,489	0,05
CIHEDO02	<—	OPLEAD04 5,797	0,064
CIHEDO02	<—	CISYMB02 4,325	0,05
CIHEDO02	<—	CISYMB03 5,208	0,058
CIHEDO03	<—	Res1 8,001	-0,099
CIHEDO03	<—	OPLEAD 6,456	-0,082
CIHEDO03	<—	OPSEEK 5,977	-0,077
CIHEDO03	<—	INWRIT 15,474	-0,091
CIHEDO03	<—	INREAD 6,487	-0,054
CIHEDO03	<—	INRECO 7,408	-0,055
CIHEDO03	<—	OPSEEK05 5,8	-0,049
CIHEDO03	<—	OPSEEK01 9,49	-0,065
CIHEDO03	<—	INREAD03 4,48	-0,04
CIHEDO03	<—	INREAD01 7,282	-0,052
CIHEDO03	<—	INRECO03 8,794	-0,057

CIHEDO03	<—	INRECO01	5,594	-0,045
CIHEDO03	<—	INWRIT03	14,137	-0,076
CIHEDO03	<—	INWRIT01	15,994	-0,08
CIHEDO03	<—	OPLEAD06	7,039	-0,058
CIHEDO03	<—	OPLEAD05	4,753	-0,046
CIHEDO03	<—	OPLEAD04	7,056	-0,063

Bootstrap (Group number 1 - Default model)

Bootstrap standard errors (Group number 1 - Default model)

Scalar Estimates (Group number 1 - Default model)

Regression Weights: (Group number 1 - Default model)

Parameter			SE	SE-SE	Mean	Bias	SE-Bias
OPLEAD	<—	CIHEDO	0,048	0,002	0,348	-0,001	0,002
OPLEAD	<—	CISYMB	0,043	0,001	0,117	0,003	0,002
OPLEAD	<—	Res1	0,055	0,002	0,945	-0,001	0,002
INWRIT	<—	OPLEAD	0,08	0,003	0,478	0	0,004
OPSEEK	<—	CIMISP	0,08	0,003	0,282	-0,004	0,004
INREAD	<—	OPSEEK	0,073	0,002	0,297	0,001	0,003
INREAD	<—	INWRIT	0,059	0,002	0,588	0,005	0,003
INRECO	<—	INWRIT	0,072	0,002	0,43	0,004	0,003
INRECO	<—	INREAD	0,064	0,002	0,341	-0,004	0,003
CIHEDO03	<—	CIHEDO	0,04	0,001	0,854	0	0,002
CIHEDO02	<—	CIHEDO	0,041	0,001	0,957	0,004	0,002
CIHEDO01	<—	CIHEDO	0	0	1	0	0
CISYMB03	<—	CISYMB	0,062	0,002	1,116	0,003	0,003
CISYMB02	<—	CISYMB	0,061	0,002	1,233	0,003	0,003
CISYMB01	<—	CISYMB	0	0	1	0	0
OPLEAD04	<—	OPLEAD	0	0	1	0	0
OPLEAD05	<—	OPLEAD	0,081	0,003	1,384	0,004	0,004
OPLEAD06	<—	OPLEAD	0,081	0,003	1,136	0,003	0,004
INWRIT01	<—	INWRIT	0	0	1	0	0
INWRIT02	<—	INWRIT	0,064	0,002	0,761	0,004	0,003
INWRIT03	<—	INWRIT	0,047	0,001	0,988	0,003	0,002
INRECO01	<—	INRECO	0	0	1	0	0
INRECO02	<—	INRECO	0,049	0,002	0,771	0,002	0,002
INRECO03	<—	INRECO	0,028	0,001	0,971	-0,001	0,001
INREAD01	<—	INREAD	0	0	1	0	0
INREAD03	<—	INREAD	0,032	0,001	1,023	0,004	0,001
INREAD04	<—	INREAD	0,046	0,001	0,827	0,002	0,002
OPSEEK01	<—	OPSEEK	0	0	1	0	0
OPSEEK04	<—	OPSEEK	0,086	0,003	1,123	0,001	0,004
OPSEEK05	<—	OPSEEK	0,093	0,003	1,326	0,003	0,004
CIMISP04	<—	CIMISP	0,112	0,004	1,313	0,009	0,005
CIMISP03	<—	CIMISP	0,103	0,003	1,118	0,003	0,005
CIMISP01	<—	CIMISP	0	0	1	0	0

Standardized Regression Weights: (Group number 1 - Default model)

Parameter			SE	SE-SE	Mean	Bias	SE-Bias
OPLEAD	<—	CIHEDO	0,049	0,002	0,42	-0,003	0,002
OPLEAD	<—	CISYMB	0,046	0,001	0,129	0,002	0,002
OPLEAD	<—	Res1	0,024	0,001	0,882	-0,002	0,001
INWRIT	<—	OPLEAD	0,053	0,002	0,341	0,001	0,002
OPSEEK	<—	CIMISP	0,065	0,002	0,254	-0,006	0,003
INREAD	<—	OPSEEK	0,048	0,002	0,205	0	0,002
INREAD	<—	INWRIT	0,046	0,001	0,543	0,002	0,002
INRECO	<—	INWRIT	0,061	0,002	0,384	0,001	0,003
INRECO	<—	INREAD	0,063	0,002	0,331	-0,003	0,003
CIHEDO03	<—	CIHEDO	0,026	0,001	0,866	0	0,001
CIHEDO02	<—	CIHEDO	0,025	0,001	0,865	-0,001	0,001
CIHEDO01	<—	CIHEDO	0,015	0	0,931	-0,001	0,001
CISYMB03	<—	CISYMB	0,018	0,001	0,909	-0,001	0,001
CISYMB02	<—	CISYMB	0,015	0	0,952	0	0,001
CISYMB01	<—	CISYMB	0,036	0,001	0,808	-0,001	0,002
OPLEAD04	<—	OPLEAD	0,035	0,001	0,767	0,001	0,002
OPLEAD05	<—	OPLEAD	0,018	0,001	0,946	0,001	0,001
OPLEAD06	<—	OPLEAD	0,033	0,001	0,798	0,001	0,001
INWRIT01	<—	INWRIT	0,026	0,001	0,908	-0,001	0,001
INWRIT02	<—	INWRIT	0,049	0,002	0,634	0,001	0,003
INWRIT03	<—	INWRIT	0,029	0,001	0,901	0	0,001
INRECO01	<—	INRECO	0,012	0	0,951	0	0,001
INRECO02	<—	INRECO	0,042	0,001	0,73	0,001	0,002
INRECO03	<—	INRECO	0,019	0,001	0,942	-0,001	0,001
INREAD01	<—	INREAD	0,017	0,001	0,936	-0,002	0,001
INREAD03	<—	INREAD	0,019	0,001	0,947	0,002	0,001
INREAD04	<—	INREAD	0,036	0,001	0,759	0,001	0,002
OPSEEK01	<—	OPSEEK	0,04	0,001	0,709	0,001	0,002

OPSEEK04	<—	OPSEEK	0,036	0,001	0,792	0	0,002
OPSEEK05	<—	OPSEEK	0,023	0,001	0,908	0	0,001
CIMISP04	<—	CIMISP	0,043	0,001	0,891	0,001	0,002
CIMISP03	<—	CIMISP	0,038	0,001	0,724	-0,001	0,002
CIMISP01	<—	CIMISP	0,04	0,001	0,673	-0,001	0,002

Covariances: (Group number 1 - Default model)

Parameter			SE	SE-SE	Mean	Bias	SE-Bias
CIHEDO	<->	CISYMB	0,089	0,003	0,326	-0,006	0,004
CIHEDO	<->	CIMISP	0,071	0,002	-0,329	0,003	0,003
CISYMB	<->	CIMISP	0,075	0,002	0,116	-0,006	0,003

Correlations: (Group number 1 - Default model)

Parameter			SE	SE-SE	Mean	Bias	SE-Bias
CIHEDO	<->	CISYMB	0,055	0,002	0,213	-0,003	0,002
CIHEDO	<->	CIMISP	0,051	0,002	-0,25	0	0,002
CISYMB	<->	CIMISP	0,061	0,002	0,097	-0,004	0,003

Variances: (Group number 1 - Default model)

Parameter	SE	SE-SE	Mean	Bias	SE-Bias
Res1	0	0	1	0	0
CIHEDO	0,147	0,005	1,681	-0,006	0,007
CISYMB	0,16	0,005	1,397	-0,003	0,007
CIMISP	0,147	0,005	1,041	0	0,007
Res3	0,17	0,005	1,968	-0,023	0,008
Res2	0,15	0,005	1,168	0,001	0,007
Res4	0,146	0,005	1,725	-0,021	0,007
Res5	0,155	0,005	1,679	-0,012	0,007
Err3	0,07	0,002	0,405	-0,005	0,003
Err2	0,092	0,003	0,514	0,004	0,004
Err1	0,05	0,002	0,257	0,001	0,002
Err6	0,065	0,002	0,359	-0,001	0,003
Err5	0,065	0,002	0,217	0	0,003
Err4	0,12	0,004	0,736	-0,001	0,005
Err10	0,103	0,003	0,8	-0,007	0,005
Err11	0,082	0,003	0,254	-0,007	0,004
Err12	0,122	0,004	0,837	-0,008	0,005
Err16	0,129	0,004	0,472	0,002	0,006
Err17	0,225	0,007	1,914	-0,023	0,01
Err18	0,141	0,004	0,501	-0,006	0,006
Err22	0,072	0,002	0,293	-0,004	0,003
Err23	0,196	0,006	1,442	-0,014	0,009
Err24	0,106	0,003	0,332	0,004	0,005
Err19	0,093	0,003	0,37	0,008	0,004
Err20	0,116	0,004	0,314	-0,012	0,005
Err21	0,17	0,005	1,309	-0,008	0,008
Err13	0,142	0,004	1,231	-0,014	0,006
Err14	0,144	0,005	0,927	-0,01	0,006
Err15	0,109	0,003	0,464	-0,002	0,005
Err9	0,176	0,006	0,457	-0,006	0,008
Err8	0,126	0,004	1,16	-0,007	0,006
Err7	0,128	0,004	1,249	-0,005	0,006

Squared Multiple Correlations: (Group number 1 - Default model)

Parameter	SE	SE-SE	Mean	Bias	SE-Bias
OPLEAD	0,043	0,001	0,221	0,003	0,002
OPSEEK	0,032	0,001	0,069	0,001	0,001
INWRIT	0,036	0,001	0,119	0,003	0,002
INREAD	0,046	0,001	0,339	0,007	0,002
INRECO	0,046	0,001	0,398	0,003	0,002
CIMISP01	0,053	0,002	0,454	0	0,002
CIMISP03	0,055	0,002	0,525	-0,001	0,002
CIMISP04	0,076	0,002	0,795	0,003	0,003
OPSEEK05	0,042	0,001	0,825	0	0,002
OPSEEK04	0,057	0,002	0,628	0,001	0,003
OPSEEK01	0,057	0,002	0,504	0,003	0,003
INREAD04	0,053	0,002	0,577	0,002	0,002
INREAD03	0,037	0,001	0,897	0,004	0,002
INREAD01	0,032	0,001	0,876	-0,003	0,001
INRECO03	0,035	0,001	0,888	-0,002	0,002
INRECO02	0,06	0,002	0,535	0,004	0,003
INRECO01	0,023	0,001	0,905	0,001	0,001
INWRIT03	0,052	0,002	0,813	0,001	0,002
INWRIT02	0,062	0,002	0,404	0,004	0,003
INWRIT01	0,047	0,001	0,826	-0,002	0,002
OPLEAD06	0,053	0,002	0,638	0,002	0,002
OPLEAD05	0,034	0,001	0,896	0,003	0,002

OPLEAD04	0,053	0,002	0,589	0,003	0,002
CISYMB01	0,056	0,002	0,655	-0,001	0,002
CISYMB02	0,028	0,001	0,907	0	0,001
CISYMB03	0,032	0,001	0,827	-0,001	0,001
CIHEDO01	0,027	0,001	0,867	-0,001	0,001
CIHEDO02	0,042	0,001	0,749	-0,001	0,002
CIHEDO03	0,045	0,001	0,751	0,001	0,002

Bootstrap Confidence (Group number 1 - Default model)

Bias-corrected percentile method (Group number 1 - Default model)

95% confidence intervals (bias-corrected percentile method)

Scalar Estimates (Group number 1 - Default model)

Regression Weights: (Group number 1 - Default model)

Parameter			Estimate	Lower	Upper	P
OPLEAD	<—	CIHEDO	0,349	0,255	0,445	0,003
OPLEAD	<—	CISYMB	0,115	0,035	0,207	0,003
OPLEAD	<—	Real	0,946	0,843	1,053	0,003
INWRIT	<—	OPLEAD	0,477	0,322	0,636	0,004
OPSEEK	<—	CIMISP	0,286	0,144	0,476	0,002
INREAD	<—	OPSEEK	0,296	0,161	0,45	0,003
INREAD	<—	INWRIT	0,583	0,471	0,695	0,005
INRECO	<—	INWRIT	0,426	0,286	0,572	0,005
INRECO	<—	INREAD	0,345	0,211	0,466	0,004
CIHEDO03	<—	CIHEDO	0,854	0,771	0,926	0,005
CIHEDO02	<—	CIHEDO	0,954	0,864	1,031	0,008
CIHEDO01	<—	CIHEDO	1	1	1	...
CISYMB03	<—	CISYMB	1,112	1,014	1,253	0,003
CISYMB02	<—	CISYMB	1,229	1,137	1,378	0,003
CISYMB01	<—	CISYMB	1	1	1	...
OPLEAD04	<—	OPLEAD	1	1	1	...
OPLEAD05	<—	OPLEAD	1,38	1,241	1,569	0,003
OPLEAD06	<—	OPLEAD	1,133	0,988	1,31	0,004
INWRIT01	<—	INWRIT	1	1	1	...
INWRIT02	<—	INWRIT	0,757	0,614	0,872	0,006
INWRIT03	<—	INWRIT	0,985	0,891	1,079	0,006
INRECO01	<—	INRECO	1	1	1	...
INRECO02	<—	INRECO	0,769	0,652	0,858	0,006
INRECO03	<—	INRECO	0,972	0,918	1,031	0,003
INREAD01	<—	INREAD	1	1	1	...
INREAD03	<—	INREAD	1,02	0,949	1,075	0,008
INREAD04	<—	INREAD	0,824	0,73	0,908	0,005
OPSEEK01	<—	OPSEEK	1	1	1	...
OPSEEK04	<—	OPSEEK	1,122	0,978	1,335	0,002
OPSEEK05	<—	OPSEEK	1,323	1,16	1,531	0,004
CIMISP04	<—	CIMISP	1,304	1,096	1,533	0,006
CIMISP03	<—	CIMISP	1,115	0,946	1,355	0,003
CIMISP01	<—	CIMISP	1	1	1	...

Standardized Regression Weights: (Group number 1 - Default model)

Parameter			Estimate	Lower	Upper	P
OPLEAD	<—	CIHEDO	0,423	0,333	0,526	0,002
OPLEAD	<—	CISYMB	0,127	0,04	0,219	0,003
OPLEAD	<—	Real	0,884	0,828	0,931	0,003
INWRIT	<—	OPLEAD	0,34	0,241	0,433	0,005
OPSEEK	<—	CIMISP	0,261	0,126	0,387	0,003
INREAD	<—	OPSEEK	0,205	0,104	0,299	0,004
INREAD	<—	INWRIT	0,541	0,452	0,622	0,005
INRECO	<—	INWRIT	0,382	0,259	0,506	0,005
INRECO	<—	INREAD	0,334	0,202	0,457	0,003
CIHEDO03	<—	CIHEDO	0,866	0,81	0,91	0,007
CIHEDO02	<—	CIHEDO	0,866	0,81	0,903	0,006
CIHEDO01	<—	CIHEDO	0,932	0,9	0,959	0,005
CISYMB03	<—	CISYMB	0,91	0,874	0,941	0,005
CISYMB02	<—	CISYMB	0,952	0,923	0,982	0,003
CISYMB01	<—	CISYMB	0,809	0,738	0,873	0,003
OPLEAD04	<—	OPLEAD	0,766	0,693	0,823	0,007
OPLEAD05	<—	OPLEAD	0,945	0,908	0,978	0,006
OPLEAD06	<—	OPLEAD	0,797	0,721	0,856	0,007
INWRIT01	<—	INWRIT	0,909	0,855	0,957	0,003
INWRIT02	<—	INWRIT	0,633	0,521	0,718	0,006
INWRIT03	<—	INWRIT	0,901	0,836	0,95	0,007
INRECO01	<—	INRECO	0,951	0,921	0,972	0,007
INRECO02	<—	INRECO	0,729	0,627	0,803	0,006
INRECO03	<—	INRECO	0,943	0,896	0,973	0,006
INREAD01	<—	INREAD	0,937	0,9	0,966	0,004

INREAD03	<—	INREAD	0,945	0,898	0,977	0,012
INREAD04	<—	INREAD	0,758	0,687	0,82	0,005
OPSEEK01	<—	OPSEEK	0,708	0,625	0,782	0,005
OPSEEK04	<—	OPSEEK	0,792	0,706	0,858	0,006
OPSEEK05	<—	OPSEEK	0,908	0,862	0,956	0,004
CIMISP04	<—	CIMISP	0,89	0,799	0,966	0,006
CIMISP03	<—	CIMISP	0,725	0,653	0,798	0,003
CIMISP01	<—	CIMISP	0,673	0,582	0,747	0,004

Covariances: (Group number 1 - Default model)

Parameter			Estimate	Lower	Upper	P
CIHEDO	<->	CISYMB	0,332	0,162	0,506	0,003
CIHEDO	<->	CIMISP	-0,332	-0,487	-0,206	0,002
CISYMB	<->	CIMISP	0,122	-0,018	0,309	0,08

Correlations: (Group number 1 - Default model)

Parameter			Estimate	Lower	Upper	P
CIHEDO	<->	CISYMB	0,216	0,103	0,323	0,003
CIHEDO	<->	CIMISP	-0,25	-0,355	-0,148	0,003
CISYMB	<->	CIMISP	0,101	-0,014	0,241	0,081

Variances: (Group number 1 - Default model)

Parameter	Estimate	Lower	Upper	P
Res1	1	1	1	...
CIHEDO	1,687	1,445	2,023	0,002
CISYMB	1,4	1,096	1,739	0,003
CIMISP	1,04	0,761	1,347	0,003
Res3	1,991	1,704	2,412	0,001
Res2	1,166	0,88	1,457	0,004
Res4	1,747	1,493	2,068	0,001
Res5	1,691	1,41	2,021	0,002
Err3	0,41	0,283	0,564	0,002
Err2	0,51	0,379	0,732	0,002
Err1	0,257	0,163	0,352	0,003
Err6	0,36	0,243	0,514	0,003
Err5	0,217	0,088	0,345	0,005
Err4	0,737	0,511	0,969	0,004
Err10	0,807	0,625	1,032	0,002
Err11	0,261	0,109	0,435	0,004
Err12	0,845	0,635	1,104	0,002
Err16	0,471	0,227	0,735	0,004
Err17	1,937	1,545	2,408	0,002
Err18	0,507	0,264	0,809	0,003
Err22	0,297	0,17	0,456	0,003
Err23	1,456	1,114	1,853	0,002
Err24	0,328	0,159	0,584	0,003
Err19	0,362	0,198	0,561	0,005
Err20	0,327	0,137	0,605	0,001
Err21	1,317	1,015	1,663	0,002
Err13	1,246	0,995	1,548	0,002
Err14	0,937	0,673	1,248	0,002
Err15	0,466	0,246	0,682	0,003
Err9	0,463	0,155	0,83	0,005
Err8	1,167	0,918	1,426	0,003
Err7	1,254	1,011	1,536	0,003

Squared Multiple Correlations: (Group number 1 - Default model)

Parameter	Estimate	Lower	Upper	P
OPLEAD	0,218	0,134	0,314	0,005
OPSEEK	0,068	0,016	0,15	0,003
INWRIT	0,116	0,058	0,187	0,005
INREAD	0,333	0,24	0,424	0,008
INRECO	0,395	0,303	0,481	0,007
CIMISP01	0,454	0,338	0,559	0,004
CIMISP03	0,526	0,426	0,637	0,003
CIMISP04	0,792	0,639	0,933	0,006
OPSEEK05	0,825	0,743	0,914	0,004
OPSEEK04	0,627	0,498	0,736	0,006
OPSEEK01	0,501	0,391	0,611	0,005
INREAD04	0,575	0,471	0,672	0,005
INREAD03	0,893	0,806	0,955	0,012
INREAD01	0,879	0,81	0,933	0,004
INRECO03	0,889	0,803	0,947	0,006
INRECO02	0,531	0,393	0,645	0,006
INRECO01	0,904	0,848	0,945	0,007
INWRIT03	0,812	0,699	0,903	0,007
INWRIT02	0,4	0,271	0,516	0,006

INWRIT01	0,827	0,732	0,915	0,003
OPLEAD06	0,635	0,521	0,733	0,007
OPLEAD05	0,893	0,825	0,957	0,006
OPLEAD04	0,587	0,481	0,677	0,007
CISYMB01	0,655	0,544	0,762	0,003
CISYMB02	0,907	0,852	0,965	0,003
CISYMB03	0,828	0,763	0,885	0,005
CIHEDO01	0,868	0,81	0,919	0,005
CIHEDO02	0,75	0,656	0,816	0,006
CIHEDO03	0,75	0,655	0,829	0,007

Minimisation History (Default model)

Iteration		Negative eigenvalues	Condition #	Smallest eigenvalue	Diameter	F	NTries	Ratio
0	e	16		-0,558	9999	8446,92	0	9999
1	e	20		-0,682	3,698	4276,52	20	0,531
2	e*	7		-0,355	0,803	2837,76	6	0,974
3	e	4		-0,377	0,446	2280,478	4	0,806
4	e*	1		-0,119	0,621	1599,245	5	0,886
5	e	0	302,559		0,814	1041,365	5	0,919
6	e	0	146,99		0,6	835,203	3	0
7	e	0	100,887		0,778	750,951	1	0,876
8	e	0	157,254		0,18	734,403	1	1,064
9	e	0	171,626		0,038	734,15	1	1,023
10	e	0	172,244		0,002	734,15	1	1,002
11	e	0	172,25		0	734,15	1	0,999

Bootstrap (Default model)

Summary of Bootstrap Iterations (Default model)

(Default model)

Iterations	Method 0	Method 1	Method 2
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
5	0	0	0
6	0	5	0
7	0	63	0
8	0	168	0
9	0	158	0
10	0	63	0
11	0	29	0
12	0	10	0
13	0	3	0
14	0	1	0
15	0	0	0
16	0	0	0
17	0	0	0
18	0	0	0
19	0	0	0
Total	0	500	0

0 bootstrap samples were unused because of a singular covariance matrix.
0 bootstrap samples were unused because a solution was not found.
500 usable bootstrap samples were obtained.

Bootstrap Distributions (Default model)

ML discrepancy (implied vs sample) (Default model)

```
                                   -----
                                   -------
                       810,647     *
                       854,078     ***
                       897,509     *****
                       940,94      **********
                       984,371     ***************
                       1027,802    ****************
                       1071,233    ******************
N = 500                1114,664    *************
Mean = 1061,491        1158,095    ***********
S. e. = 4,535          1201,526    ********
                       1244,957    ****
                       1288,388    *
                       1331,819    *
                       1375,25     *
                       1418,681    *
```

```
                             ---
                             ---
```

ML discrepancy (implied vs pop) (Default model)

```
                             ---
                             ---
                 794,52      *
                 817,08      ****
                 839,64      *********
                 862,2       *******************
                 884,76      ****************
                 907,32      *************
                 929,88      *******
N = 500          952,44      ****
Mean = 886,151   975         **
S. e. = 1,865    997,56      *
                 1020,119
                 1042,679    *
                 1065,239    *
                 1087,799    *
                 1110,359    *
                             ---
                             ---
```

K-L overoptimism (unstabilized) (Default model)

```
                             ---
                             ---
                 -957,817    *
                 -742,145    **
                 -526,473    *****
                 -310,8      ********
                 -95,128     ***************
                 120,544     *****************
                 336,216     ********************
N = 500          551,888     *****************
Mean = 297,018   767,561     ***********
S. e. = 20,177   983,233     ******
                 1198,905    ***
                 1414,577    *
                 1630,35     *
                 1845,922
                 2061,594    *
                             ---
                             ---
```

K-L overoptimism (stabilised) (Default model)

```
                             ---
                             ---
                 -21,905     *
                 39,746      **
                 101,396     *****
                 163,046     ***********
                 224,697     ****************
                 286,347     *****************
                 347,998     ******************
N = 500          409,648     **********
Mean = 295,726   471,298     ****
S. e. = 5,309    532,949     **
                 594,599     **
                 656,25      *
                 717,9
                 779,55      *
                 841,201     *
                             ---
                             ---
```

ML discrepancy (implied vs pop) (Default model)

```
                             ---
                             ---
                 794,52      *
                 817,08      ****
                 839,64      *********
                 862,2       *******************
                 884,76      ****************
                 907,32      *************
                 929,88      *******
N = 500          952,44      ****
```

Mean = 886,151	975	**
S. e. = 1,865	997,56	*
	1020,119	
	1042,679	*
	1065,239	*
	1087,799	*
	1110,359	*

Model Fit Summary

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	59	734,15	241	0	3,046
Saturated model	300	0	0		
Independence model	24	8370,766	276	0	30,329

RMR, GFI

Model	RMR	GFI	AGFI	PGFI
Default model	0,235	0,878	0,848	0,705
Saturated model	0	1		
Independence model	0,751	0,335	0,277	0,308

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	0,912	0,9	0,939	0,93	0,939
Saturated model	1		1		1
Independence model	0	0	0	0	0

Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default model	0,873	0,797	0,82
Saturated model	0	0	0
Independence model	1	0	0

NCP

Model	NCP	LO 90	HI 90
Default model	493,15	415,43	578,487
Saturated model	0	0	0
Independence model	8094,766	7799,459	8396,421

FMIN

Model	FMIN	F0	LO 90	HI 90
Default model	1,546	1,038	0,875	1,218
Saturated model	0	0	0	0
Independence model	17,623	17,042	16,42	17,677

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	0,066	0,06	0,071	0
Independence model	0,248	0,244	0,253	0

AIC

Model	AIC	BCC	BIC	CAIC
Default model	852,15	858,705	1097,909	1156,909
Saturated model	600	633,333	1849,625	2149,625
Independence model	8418,766	8421,432	8518,736	8542,736

ECVI

Model	ECVI	LO 90	HI 90	MECVI
Default model	1,794	1,63	1,974	1,808
Saturated model	1,263	1,263	1,263	1,333

Independence model	17,724	17,102	18,359	17,729

HOELTER

Model	HOELTER .05	HOELTER .01
Default model	181	191
Independence model	18	19

Execution time summary

Minimization:	0,031
Miscellaneous:	0,188
Bootstrap:	2,781
Total:	3

A.2 Survey AON

Analysis Summary

Date and Time

Date: Dienstag, 11. April 2006
Time: 12:22:39

Title

model_aon_bootstrapped: Dienstag, 11. April 2006 12:22

Groups

Group number 1 (Group number 1)

Notes for Group (Group number 1)

The model is recursive.
Sample size = 345

Variable Summary (Group number 1)

Your model contains the following variables (Group number 1)

Observed, endogenous variables
CIHEDO03
CIHEDO02
CIHEDO01
CISYMB03
CISYMB02
CISYMB01
OPLEAD04
OPLEAD05
OPLEAD06
INWRIT01
INWRIT02
INWRIT03
INRECO01
INRECO02
INRECO03
INREAD01
INREAD03
INREAD04
OPSEEK01
OPSEEK04
OPSEEK05
CIMISP04
CIMISP03
CIMISP01
Unobserved, endogenous variables
OPLEAD
INWRIT
INRECO
INREAD

OPSEEK
Unobserved, exogenous variables
CIHEDO
Err3
Err2
Err1
CISYMB
Err6
Err5
Err4
Err10
Err11
Err12
Res1
Err16
Err17
Err18
Res3
Err22
Err23
Err24
Res5
Err19
Err20
Err21
Res4
Err13
Err14
Err15
CIMISP
Err9
Err8
Err7
Res2

Variable counts (Group number 1)

Number of variables in your model:	61
Number of observed variables:	24
Number of unobserved variables:	37
Number of exogenous variables:	32
Number of endogenous variables:	29

Parameter summary (Group number 1)

	Weights	Covariances	Variances	Means	Intercepts	Total
Fixed	36	0	1	0	0	37
Labeled	0	0	0	0	0	0
Unlabeled	25	3	31	0	0	59
Total	61	3	32	0	0	96

Assessment of normality (Group number 1)

Variable	min	max	skew	c.r.	kurtosis	c.r.
CIMISP01	1	7	0,058	0,437	-0,604	-2,29
CIMISP03	1	7	0,254	1,923	-0,456	-1,73
CIMISP04	1	7	0,072	0,544	-0,449	-1,703
OPSEEK05	1	7	0,222	1,682	-0,835	-3,165
OPSEEK04	1	7	0,017	0,131	-0,897	-3,4
OPSEEK01	1	7	0,22	1,671	-0,65	-2,466
INREAD04	1	7	-0,32	-2,423	-0,763	-2,893
INREAD03	1	7	-0,33	-2,499	-0,798	-3,024
INREAD01	1	7	-0,381	-2,889	-0,736	-2,789
INRECO03	1	7	-0,039	-0,298	-0,863	-3,274
INRECO02	1	7	-0,183	-1,384	-0,735	-2,787
INRECO01	1	7	-0,058	-0,436	-0,886	-3,36
INWRIT03	1	7	0,158	1,197	-0,898	-3,407
INWRIT02	1	7	0,016	0,124	-0,909	-3,445
INWRIT01	1	7	0,188	1,428	-0,788	-2,986
OPLEAD06	1	7	0,244	1,848	-0,849	-3,218
OPLEAD05	1	7	0,217	1,642	-0,81	-3,072
OPLEAD04	1	7	0,001	0,007	-0,793	-3,005
CISYMB01	1	7	-0,388	-2,942	-0,176	-0,666
CISYMB02	1	7	-0,393	-2,979	-0,459	-1,739

CISYMB03	1	7	-0,457	-3,462	-0,147	-0,559
CIHEDO01	1	7	-0,524	-3,971	-0,258	-0,977
CIHEDO02	1	7	-0,547	-4,149	-0,219	-0,829
CIHEDO03	1	7	-0,843	-6,392	0,294	1,114
Multivariate					169.168	44.472

Observations farthest from the centroid (Mahalanobis distance) (Group number 1)

Observation number	Mahalanobis d-squared	p1	p2
16	100,954	0	0
248	76,133	0	0
45	75,519	0	0
140	72,38	0	0
340	68,556	0	0
119	65,91	0	0
41	63,461	0	0
79	61,69	0	0
285	61,339	0	0
24	60,355	0	0
316	60,084	0	0
63	59,435	0	0
219	58,84	0	0
151	54,828	0	0
69	53,601	0	0
115	53,44	0,001	0
263	52,749	0,001	0
294	52,586	0,001	0
296	52,208	0,001	0
110	50,687	0,001	0
293	49,87	0,001	0
197	49,566	0,002	0
106	49,192	0,002	0
122	48,868	0,002	0
67	48,193	0,002	0
292	48,094	0,002	0
27	47,98	0,003	0
177	47,832	0,003	0
46	47,52	0,003	0
313	46,275	0,004	0
345	44,804	0,006	0
23	44,466	0,007	0
179	43,812	0,008	0
235	43,548	0,009	0
180	43,291	0,009	0
321	43,278	0,009	0
310	43,092	0,01	0
201	43,073	0,01	0
341	43,028	0,01	0
43	41,313	0,015	0
169	40,815	0,017	0
157	40,804	0,018	0
105	39,855	0,022	0
51	39,695	0,023	0
220	39,299	0,025	0
199	38,462	0,031	0
255	37,948	0,035	0
131	37,524	0,039	0
230	37,391	0,04	0
200	37,038	0,043	0
174	36,892	0,045	0
92	36,87	0,045	0
290	36,783	0,046	0
283	36,437	0,05	0
7	36,37	0,051	0
25	36,279	0,052	0
173	36,193	0,053	0
117	35,753	0,058	0
281	35,48	0,062	0
338	35,455	0,062	0
8	35,204	0,065	0
135	35,158	0,066	0
196	35,087	0,067	0
257	34,943	0,069	0
137	34,438	0,077	0
262	34,308	0,079	0
291	34,291	0,08	0
121	34,223	0,081	0
207	33,746	0,089	0
28	33,73	0,09	0

213	33,682	0,09	0
264	33,521	0,094	0
183	33,502	0,094	0
261	33,419	0,096	0
206	33,408	0,096	0
168	33,198	0,1	0
241	33,088	0,102	0
68	33,07	0,103	0
103	33,014	0,104	0
217	32,528	0,114	0
87	32,35	0,119	0
75	32,073	0,125	0
329	31,772	0,133	0
145	31,723	0,134	0
76	31,391	0,143	0
100	31,346	0,144	0
165	31,303	0,145	0
338	31,159	0,149	0
21	31,102	0,151	0
49	30,708	0,162	0
149	29,961	0,186	0
309	29,93	0,187	0
221	29,887	0,189	0
249	29,821	0,191	0
161	29,738	0,194	0
325	29,683	0,195	0
270	29,359	0,207	0,001
222	29,299	0,209	0,001
72	29,146	0,215	0,001
48	29,104	0,216	0,001

Models

Default model (Default model)

Notes for Model (Default model)

Computation of degrees of freedom (Default model)

Number of distinct sample moments:	300
Number of distinct parameters to be estimated:	59
Degrees of freedom (300 - 59):	241

Result (Default model)

Minimum was achieved
Chi-square = 696,387
Degrees of freedom = 241
Probability level = ,000

Group number 1 (Group number 1 - Default model)

Estimates (Group number 1 - Default model)

Scalar Estimates (Group number 1 - Default model)

Maximum Likelihood Estimates

Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
OPLEAD	<—	CIHEDO	0,335	0,046	7,287	***	
OPLEAD	<—	CISYMB	0,238	0,055	4,32	***	
OPLEAD	<—	Res1	1,035	0,062	16,779	***	
INWRIT	<—	OPLEAD	0,404	0,076	5,316	***	
OPSEEK	<—	CIMISP	0,27	0,073	3,724	***	
INREAD	<—	OPSEEK	0,462	0,061	7,577	***	
INREAD	<—	INWRIT	0,582	0,066	8,861	***	
INRECO	<—	INWRIT	0,443	0,08	5,549	***	
INRECO	<—	INREAD	0,313	0,063	4,948	***	
CIHEDO03	<—	CIHEDO	0,916	0,037	25,069	***	
CIHEDO02	<—	CIHEDO	0,947	0,04	23,789	***	
CIHEDO01	<—	CIHEDO	1				
CISYMB03	<—	CISYMB	1,154	0,058	19,923	***	
CISYMB02	<—	CISYMB	1,222	0,061	20,01	***	
CISYMB01	<—	CISYMB	1				

OPLEAD04	<—	OPLEAD	1			
OPLEAD05	<—	OPLEAD	1,271	0,066	19,28	***
OPLEAD06	<—	OPLEAD	1,188	0,063	18,963	***
INWRIT01	<—	INWRIT	1			
INWRIT02	<—	INWRIT	0,736	0,078	9,445	***
INWRIT03	<—	INWRIT	0,603	0,077	7,847	***
INRECO01	<—	INRECO	1			
INRECO02	<—	INRECO	0,607	0,053	11,504	***
INRECO03	<—	INRECO	0,915	0,042	21,603	***
INREAD01	<—	INREAD	1			
INREAD03	<—	INREAD	1,049	0,032	33,09	***
INREAD04	<—	INREAD	0,605	0,053	11,492	***
OPSEEK01	<—	OPSEEK	1			
OPSEEK04	<—	OPSEEK	1,172	0,058	20,332	***
OPSEEK05	<—	OPSEEK	1,164	0,058	20,095	***
CIMISP04	<—	CIMISP	1,33	0,094	14,104	***
CIMISP03	<—	CIMISP	1,257	0,09	13,994	***
CIMISP01	<—	CIMISP	1			

Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
OPLEAD	<—	CIHEDO	0,407
OPLEAD	<—	CISYMB	0,235
OPLEAD	<—	Res1	0,86
INWRIT	<—	OPLEAD	0,329
OPSEEK	<—	CIMISP	0,224
INREAD	<—	OPSEEK	0,369
INREAD	<—	INWRIT	0,545
INRECO	<—	INWRIT	0,396
INRECO	<—	INREAD	0,298
CIHEDO03	<—	CIHEDO	0,897
CIHEDO02	<—	CIHEDO	0,872
CIHEDO01	<—	CIHEDO	0,92
CISYMB03	<—	CISYMB	0,913
CISYMB02	<—	CISYMB	0,918
CISYMB01	<—	CISYMB	0,807
OPLEAD04	<—	OPLEAD	0,791
OPLEAD05	<—	OPLEAD	0,923
OPLEAD06	<—	OPLEAD	0,902
INWRIT01	<—	INWRIT	0,857
INWRIT02	<—	INWRIT	0,592
INWRIT03	<—	INWRIT	0,479
INRECO01	<—	INRECO	0,971
INRECO02	<—	INRECO	0,562
INRECO03	<—	INRECO	0,874
INREAD01	<—	INREAD	0,941
INREAD03	<—	INREAD	0,98
INREAD04	<—	INREAD	0,543
OPSEEK01	<—	OPSEEK	0,829
OPSEEK04	<—	OPSEEK	0,906
OPSEEK05	<—	OPSEEK	0,894
CIMISP04	<—	CIMISP	0,915
CIMISP03	<—	CIMISP	0,837
CIMISP01	<—	CIMISP	0,698

Covariances: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
CIHEDO	<->	CISYMB	0,354	0,104	3,401	***	
CIHEDO	<->	CIMISP	-0,198	0,092	-2,161	0,031	
CISYMB	<->	CIMISP	0,259	0,077	3,374	***	

Correlations: (Group number 1 - Default model)

			Estimate
CIHEDO	<->	CISYMB	0,204
CIHEDO	<->	CIMISP	-0,13
CISYMB	<->	CIMISP	0,209

Variances: (Group number 1 - Default model)

	Estimate	S.E.	C.R.	P	Label
Res1	1				
CIHEDO	2,14	0,196	10,912	***	
CISYMB	1,409	0,159	8,861	***	
CIMISP	1,089	0,154	7,055	***	
Res3	1,938	0,25	7,741	***	
Res2	1,504	0,165	9,124	***	
Res4	1,402	0,143	9,79	***	
Res5	1,702	0,171	9,968	***	

Err3	0,438	0,052	8,46	***
Err2	0,603	0,063	9,621	***
Err1	0,387	0,055	7	***
Err6	0,375	0,056	6,701	***
Err5	0,391	0,062	6,344	***
Err4	0,755	0,068	11,019	***
Err10	0,866	0,077	11,204	***
Err11	0,408	0,068	5,994	***
Err12	0,466	0,064	7,301	***
Err16	0,789	0,173	4,562	***
Err17	2,185	0,195	11,202	***
Err18	2,644	0,218	12,14	***
Err22	0,168	0,092	1,829	0,067
Err23	2,174	0,171	12,717	***
Err24	0,706	0,094	7,549	***
Err19	0,318	0,057	5,586	***
Err20	0,114	0,057	1,994	0,046
Err21	2,16	0,167	12,927	***
Err13	0,723	0,07	10,312	***
Err14	0,475	0,068	6,953	***
Err15	0,537	0,07	7,618	***
Err9	0,374	0,089	4,217	***
Err8	0,736	0,094	7,829	***
Err7	1,144	0,1	11,417	***

Squared Multiple Correlations: (Group number 1 - Default model)

	Estimate
OPLEAD	0,26
OPSEEK	0,05
INWRIT	0,109
INREAD	0,434
INRECO	0,375
CIMISP01	0,487
CIMISP03	0,7
CIMISP04	0,837
OPSEEK05	0.8
OPSEEK04	0,821
OPSEEK01	0,687
INREAD04	0,295
INREAD03	0,96
INREAD01	0,886
INRECO03	0,764
INRECO02	0,316
INRECO01	0,942
INWRIT03	0,23
INWRIT02	0,35
INWRIT01	0,734
OPLEAD06	0,814
OPLEAD05	0,852
OPLEAD04	0,626
CISYMB01	0,651
CISYMB02	0,843
CISYMB03	0,833
CIHEDO01	0,847
CIHEDO02	0,761
CIHEDO03	0,804

Modification Indices (Group number 1 - Default model)

Covariances: (Group number 1 - Default model)

			M.I.	Par Change
Res2	<->	Res1	44,9	0,496
Res2	<->	CISYMB	7,137	0.219
Res3	<->	CIMISP	7,107	0,241
Res3	<->	Res2	18,896	0,473
Res4	<->	CIHEDO	8,94	0,306
Err7	<->	CISYMB	7,472	-0,197
Err7	<->	CIHEDO	5,237	0,205
Err8	<->	CISYMB	19,186	0,275
Err8	<->	CIHEDO	5,598	-0,185
Err9	<->	CISYMB	6,298	-0,144
Err15	<->	CIMISP	5,436	0,121
Err15	<->	CIHEDO	11,507	-0,241
Err14	<->	CIMISP	9,892	-0,159
Err13	<->	Res1	8,336	0,156
Err13	<->	CIHEDO	5.115	0,169
Err21	<->	Res1	5,973	-0,208
Err21	<->	CIHEDO	8,903	-0,35

Err21	<->	Res2	5,585	-0,243
Err21	<->	Res3	10,605	0,407
Err20	<->	Err13	5,553	-0,074
Err19	<->	Err13	5,738	0,078
Err24	<->	Err15	6,759	0,115
Err24	<->	Err13	11,79	-0,159
Err23	<->	CIHEDO	4,433	-0,249
Err23	<->	Err14	4,235	0,145
Err23	<->	Err13	6,579	-0,194
Err23	<->	Err21	25,722	0,603
Err22	<->	CIHEDO	4,637	0,145
Err22	<->	Err13	17,375	0,176
Err22	<->	Err21	6,75	-0,172
Err18	<->	CIMISP	4,632	-0,207
Err18	<->	CISYMB	4,546	-0,227
Err18	<->	Res5	5,185	-0,285
Err18	<->	Err21	25,868	0,676
Err18	<->	Err20	4,261	-0,116
Err18	<->	Err23	14,491	0,512
Err17	<->	Res1	6,96	-0,236
Err17	<->	CIHEDO	10,363	-0,398
Err17	<->	Err13	6,44	-0,2
Err17	<->	Err21	41,713	0,802
Err17	<->	Err20	5,107	-0,118
Err17	<->	Err23	36,969	0,761
Err17	<->	Err18	69,813	1,17
Err16	<->	CIMISP	12,459	0,257
Err16	<->	Res2	19,138	0,384
Err16	<->	Err21	12,297	-0,354
Err16	<->	Err23	38,165	-0,628
Err16	<->	Err22	6,12	0,139
Err16	<->	Err18	9,88	-0,348
Err12	<->	Err7	10,435	-0,164
Err12	<->	Err15	5,23	0,092
Err11	<->	Err7	10,168	0,165
Err11	<->	Err15	4,601	-0,088
Err11	<->	Err23	5,332	0,158
Err10	<->	Err19	5,075	0,078
Err10	<->	Err23	4,329	-0,167
Err4	<->	CIMISP	9,206	0,164
Err4	<->	Err7	4,859	0,125
Err4	<->	Err10	4,695	0,109
Err5	<->	Err19	4,659	0,06
Err6	<->	Res2	4,034	0,108
Err6	<->	Err7	4,328	-0,098
Err6	<->	Err19	4,298	-0,056
Err6	<->	Err12	4,11	0,071
Err1	<->	Res5	4,806	0,131
Err1	<->	Err7	7,351	0,132
Err1	<->	Err15	4,219	-0,079
Err1	<->	Err5	7,57	-0,096
Err2	<->	CISYMB	10,408	0,182
Err2	<->	Err13	4,903	0,099
Err2	<->	Err10	4,157	0,097
Err3	<->	Res2	4,028	-0,11
Err3	<->	Err13	5,714	-0,095
Err3	<->	Err12	5,544	0,083

Variances: (Group number 1 - Default model)

			M.I.	Par Change

Regression Weights: (Group number 1 - Default model)

			M.I.	Par Change
OPSEEK	<—	Res1	44,9	0,496
OPSEEK	<—	CISYMB	7,803	0,17
OPSEEK	<—	OPLEAD	45,805	0,406
OPSEEK	<—	INWRIT	41,05	0,334
INWRIT	<—	CIMISP	9,103	0,258
INWRIT	<—	OPSEEK	23,853	0,343
INREAD	<—	CIHEDO	9,14	0,149
INRECO	<—	OPLEAD	5,024	0,145
CIMISP01	<—	CISYMB	4,756	-0,116
CIMISP01	<—	INREAD	5,305	-0,09
CIMISP01	<—	INREAD04	4,643	-0,075
CIMISP01	<—	INREAD03	5,589	-0,085
CIMISP01	<—	CISYMB02	4,774	-0,084
CIMISP01	<—	CISYMB03	6,697	-0,105

CIMISP01	<—	CIHEDO01 5,302	0,088
CIMISP03	<—	CISYMB 14,498	0,177
CIMISP03	<—	CISYMB01 14,217	0,136
CIMISP03	<—	CISYMB02 13,315	0,123
CIMISP03	<—	CISYMB03 12,225	0,124
CIMISP04	<—	CISYMB 5,62	-0,101
CIMISP04	<—	CISYMB01 4,257	-0,068
CIMISP04	<—	CISYMB02 6,319	-0,077
CIMISP04	<—	CISYMB03 4,046	-0,065
OPSEEK05	<—	CIMISP 9,538	0,151
OPSEEK05	<—	CIHEDO 12,918	-0,123
OPSEEK05	<—	CIMISP03 8,044	0,088
OPSEEK05	<—	CIMISP04 9,092	0,096
OPSEEK05	<—	INRECO03 7,669	0,077
OPSEEK05	<—	CIHEDO01 14,551	-0,116
OPSEEK05	<—	CIHEDO02 10,265	-0,098
OPSEEK05	<—	CIHEDO03 8,718	-0,096
OPSEEK04	<—	CIMISP 11,219	-0,16
OPSEEK04	<—	CIMISP03 9,88	-0,095
OPSEEK04	<—	CIMISP04 11,233	-0,104
OPSEEK04	<—	INWRIT03 5,395	0,059
OPSEEK01	<—	Res1 8,336	0,156
OPSEEK01	<—	CIHEDO 5,633	0,085
OPSEEK01	<—	OPLEAD 13,545	0,161
OPSEEK01	<—	OPLEAD06 10,48	0,104
OPSEEK01	<—	OPLEAD05 13,626	0,113
OPSEEK01	<—	OPLEAD04 8,707	0,098
OPSEEK01	<—	CIHEDO01 5,598	0,075
OPSEEK01	<—	CIHEDO02 8,692	0,094
INREAD04	<—	Res1 5,973	-0,208
INREAD04	<—	CISYMB 6,309	-0,175
INREAD04	<—	CIHEDO 10,24	-0,181
INREAD04	<—	OPLEAD 15,593	-0,272
INREAD04	<—	OPSEEK 6,842	-0,173
INREAD04	<—	OPSEEK05 5,361	-0,113
INREAD04	<—	OPSEEK04 5,919	-0,119
INREAD04	<—	OPSEEK01 6,44	-0,133
INREAD04	<—	INRECO02 18,737	0,194
INREAD04	<—	INWRIT03 25,482	0,217
INREAD04	<—	INWRIT02 33,821	0,253
INREAD04	<—	OPLEAD06 9,718	-0,157
INREAD04	<—	OPLEAD05 15,807	-0,191
INREAD04	<—	OPLEAD04 16,484	-0,213
INREAD04	<—	CISYMB02 7,642	-0,14
INREAD04	<—	CIHEDO01 8,165	-0,143
INREAD04	<—	CIHEDO02 10,289	-0,161
INREAD04	<—	CIHEDO03 7,501	-0,146
INREAD03	<—	INWRIT03 4,429	-0,038
INREAD03	<—	INWRIT02 4,635	-0,039
INREAD01	<—	CIHEDO02 4,603	0,047
INRECO02	<—	CIHEDO 4,159	-0,116
INRECO02	<—	OPLEAD 4,173	-0,142
INRECO02	<—	OPSEEK 4,1	-0,135
INRECO02	<—	OPSEEK05 4,823	-0,108
INRECO02	<—	OPSEEK01 8,439	-0,154
INRECO02	<—	INREAD04 14,862	0,177
INRECO02	<—	INWRIT03 8,211	0,124
INRECO02	<—	INWRIT02 17,466	0,183
INRECO02	<—	INWRIT01 8,533	-0,136
INRECO02	<—	OPLEAD06 5,541	-0,119
INRECO02	<—	OPLEAD04 7,526	-0,145
INRECO02	<—	CIHEDO02 6,137	-0,125
INRECO01	<—	CIHEDO 5,676	0,076
INRECO01	<—	OPSEEK01 11,239	0,099
INRECO01	<—	INREAD04 4,523	-0,054
INRECO01	<—	CIHEDO01 5,612	0,067
INRECO01	<—	CIHEDO03 5,528	0,07
INWRIT03	<—	CIMISP 6,535	-0,233
INWRIT03	<—	CISYMB 8,37	-0,228
INWRIT03	<—	INRECO 4,719	-0,122
INWRIT03	<—	CIMISP03 5,143	-0,131
INWRIT03	<—	CIMISP04 5,633	-0,141
INWRIT03	<—	OPSEEK05 5,03	-0,123
INWRIT03	<—	OPSEEK01 4,542	-0,127
INWRIT03	<—	INREAD04 11,997	0,178
INWRIT03	<—	INRECO03 6,975	-0,138
INWRIT03	<—	INRECO01 4,837	-0,117
INWRIT03	<—	INWRIT02 41,108	0,315
INWRIT03	<—	CISYMB01 4,879	-0,135
INWRIT03	<—	CISYMB02 8,578	-0,167
INWRIT03	<—	CISYMB03 6,601	-0,154

INWRIT02	<—	Res1	6,96	-0,236
INWRIT02	<—	CIHEDO	9,904	-0,187
INWRIT02	<—	OPLEAD	14,464	-0,276
INWRIT02	<—	OPSEEK01	5,423	-0,129
INWRIT02	<—	INREAD04	19,732	0,213
INWRIT02	<—	INRECO02	17,62	0,198
INWRIT02	<—	INWRIT03	51,134	0,324
INWRIT02	<—	OPLEAD06	14,623	-0,203
INWRIT02	<—	OPLEAD05	9,941	-0,16
INWRIT02	<—	OPLEAD04	15,299	-0,216
INWRIT02	<—	CIHEDO01	9,557	-0,163
INWRIT02	<—	CIHEDO02	7,331	-0,143
INWRIT02	<—	CIHEDO03	7,398	-0,153
INWRIT01	<—	CIMISP	15,865	0,275
INWRIT01	<—	CISYMB	4,222	0,123
INWRIT01	<—	OPSEEK	26,263	0,29
INWRIT01	<—	INREAD	9,859	0,138
INWRIT01	<—	INRECO	4,058	0,085
INWRIT01	<—	CIMISP03	16,041	0,174
INWRIT01	<—	CIMISP04	13,181	0,163
INWRIT01	<—	OPSEEK05	21,128	0,191
INWRIT01	<—	OPSEEK04	19,494	0,185
INWRIT01	<—	OPSEEK01	25,758	0,228
INWRIT01	<—	INREAD03	10,354	0,13
INWRIT01	<—	INREAD01	8,1	0,116
INWRIT01	<—	INRECO02	15,607	-0,151
INWRIT01	<—	INRECO01	4,86	0,088
INWRIT01	<—	INWRIT03	7,62	-0,102
INWRIT01	<—	CISYMB03	4,669	0,098
OPLEAD06	<—	CIMISP01	5,665	-0,072
OPLEAD05	<—	CIMISP01	4,323	0,064
OPLEAD05	<—	INRECO02	4,54	0,055
CISYMB01	<—	CIMISP	8,956	0,153
CISYMB01	<—	CIMISP01	12,075	0,117
CISYMB01	<—	CIMISP03	9,47	0,099
CISYMB01	<—	CIMISP04	6,151	0,083
CISYMB03	<—	OPLEAD06	5,185	0,06
CIHEDO01	<—	CIMISP01	4,981	0,064
CIHEDO02	<—	CISYMB	10,51	0,135
CIHEDO02	<—	INREAD	4,143	0,063
CIHEDO02	<—	INREAD01	5,657	0,068
CIHEDO02	<—	OPLEAD04	4,837	0,069
CIHEDO02	<—	CISYMB01	8,02	0,092
CIHEDO02	<—	CISYMB02	11,419	0,102
CIHEDO02	<—	CISYMB03	7,401	0,086
CIHEDO03	<—	OPSEEK	5,291	-0,081
CIHEDO03	<—	OPSEEK01	9,212	-0,085

Bootstrap (Group number 1 - Default model)

Bootstrap standard errors (Group number 1 - Default model)

Scalar Estimates (Group number 1 - Default model)

Regression Weights: (Group number 1 - Default model)

Parameter			SE	SE-SE	Mean	Bias	SE-Bias
OPLEAD	<—	CIHEDO	0,041	0,001	0,334	-0,001	0,002
OPLEAD	<—	CISYMB	0,058	0,002	0,234	-0,004	0,003
OPLEAD	<—	Res1	0,059	0,002	1,032	-0,004	0,003
INWRIT	<—	OPLEAD	0,136	0,004	0,377	-0,027	0,006
OPSEEK	<—	CIMISP	0,092	0,003	0,271	0	0,004
INREAD	<—	OPSEEK	0,099	0,003	0,482	0,02	0,004
INREAD	<—	INWRIT	0,078	0,002	0,573	-0,009	0,003
INRECO	<—	INWRIT	0,105	0,003	0,412	-0,031	0,005
INRECO	<—	INREAD	0,083	0,003	0,341	0,028	0,004
CIHEDO03	<—	CIHEDO	0,042	0,001	0,913	-0,004	0,002
CIHEDO02	<—	CIHEDO	0,049	0,002	0,946	-0,001	0,002
CIHEDO01	<—	CIHEDO	0	0	1	0	0
CISYMB03	<—	CISYMB	0,079	0,002	1,162	0,008	0,004
CISYMB02	<—	CISYMB	0,076	0,002	1,229	0,007	0,003
CISYMB01	<—	CISYMB	0	0	1	0	0
OPLEAD04	<—	OPLEAD	0	0	1	0	0
OPLEAD05	<—	OPLEAD	0,068	0,002	1,276	0,004	0,003
OPLEAD06	<—	OPLEAD	0,065	0,002	1,192	0,005	0,003
INWRIT01	<—	INWRIT	0	0	1	0	0
INWRIT02	<—	INWRIT	0,302	0,01	0,821	0,085	0,014
INWRIT03	<—	INWRIT	0,284	0,009	0,679	0,077	0,013
INRECO01	<—	INRECO	0	0	1	0	0
INRECO02	<—	INRECO	0,075	0,002	0,609	0,002	0,003
INRECO03	<—	INRECO	0,051	0,002	0,916	0	0,002

INREAD01	<—	INREAD	0	0	1	0	0
INREAD03	<—	INREAD	0,027	0,001	1,049	0	0,001
INREAD04	<—	INREAD	0,065	0,002	0,606	0,002	0,003
OPSEEK01	<—	OPSEEK	0	0	1	0	0
OPSEEK04	<—	OPSEEK	0,053	0,002	1,173	0,001	0,002
OPSEEK05	<—	OPSEEK	0,063	0,002	1,167	0,003	0,003
CIMISP04	<—	CIMISP	0,095	0,003	1,333	0,003	0,004
CIMISP03	<—	CIMISP	0,117	0,004	1,27	0,013	0,005
CIMISP01	<—	CIMISP	0	0	1	0	0

Standardised Regression Weights: (Group number 1 - Default model)

Parameter			SE	SE-SE	Mean	Bias	SE-Bias
OPLEAD	<—	CIHEDO	0,047	0,001	0,407	0	0,002
OPLEAD	<—	CISYMB	0,052	0,002	0,23	-0,005	0,002
OPLEAD	<—	Res1	0,026	0,001	0,859	-0,001	0,001
INWRIT	<—	OPLEAD	0,098	0,003	0,307	-0,023	0,004
OPSEEK	<—	CIMISP	0,069	0,002	0,222	-0,002	0,003
INREAD	<—	OPSEEK	0,07	0,002	0,381	0,012	0,003
INREAD	<—	INWRIT	0,092	0,003	0,521	-0,025	0,004
INRECO	<—	INWRIT	0,104	0,003	0,362	-0,033	0,005
INRECO	<—	INREAD	0,085	0,003	0,328	0,029	0,004
CIHEDO03	<—	CIHEDO	0,019	0,001	0,896	-0,001	0,001
CIHEDO02	<—	CIHEDO	0,028	0,001	0,873	0,001	0,001
CIHEDO01	<—	CIHEDO	0,016	0,001	0,922	0,002	0,001
CISYMB03	<—	CISYMB	0,024	0,001	0,915	0,002	0,001
CISYMB02	<—	CISYMB	0,02	0,001	0,919	0,001	0,001
CISYMB01	<—	CISYMB	0,04	0,001	0,806	-0,001	0,002
OPLEAD04	<—	OPLEAD	0,032	0,001	0,791	0	0,001
OPLEAD05	<—	OPLEAD	0,018	0,001	0,923	0	0,001
OPLEAD06	<—	OPLEAD	0,018	0,001	0,903	0,001	0,001
INWRIT01	<—	INWRIT	0,101	0,003	0,834	-0,023	0,005
INWRIT02	<—	INWRIT	0,121	0,004	0,616	0,024	0,005
INWRIT03	<—	INWRIT	0,126	0,004	0,501	0,021	0,006
INRECO01	<—	INRECO	0,02	0,001	0,97	0	0,001
INRECO02	<—	INRECO	0,064	0,002	0,564	0,002	0,003
INRECO03	<—	INRECO	0,035	0,001	0,874	0	0,002
INREAD01	<—	INREAD	0,019	0,001	0,943	0,002	0,001
INREAD03	<—	INREAD	0,012	0	0,98	0	0,001
INREAD04	<—	INREAD	0,058	0,002	0,547	0,004	0,003
OPSEEK01	<—	OPSEEK	0,029	0,001	0,83	0,001	0,001
OPSEEK04	<—	OPSEEK	0,022	0,001	0,905	0	0,001
OPSEEK05	<—	OPSEEK	0,023	0,001	0,895	0	0,001
CIMISP04	<—	CIMISP	0,026	0,001	0,913	-0,002	0,001
CIMISP03	<—	CIMISP	0,035	0,001	0,84	0,003	0,002
CIMISP01	<—	CIMISP	0,041	0,001	0,696	-0,002	0,002

Covariances: (Group number 1 - Default model)

Parameter			SE	SE-SE	Mean	Bias	SE-Bias
CIHEDO	<->	CISYMB	0,121	0,004	0,355	0,001	0,005
CIHEDO	<->	CIMISP	0,103	0,003	-0,191	0,007	0,005
CISYMB	<->	CIMISP	0,098	0,003	0,259	0	0,004

Correlations: (Group number 1 - Default model)

Parameter			SE	SE-SE	Mean	Bias	SE-Bias
CIHEDO	<->	CISYMB	0,068	0,002	0,205	0,001	0,003
CIHEDO	<->	CIMISP	0,068	0,002	-0,126	0,004	0,003
CISYMB	<->	CIMISP	0,075	0,002	0,21	0	0,003

Variances: (Group number 1 - Default model)

Parameter	SE	SE-SE	Mean	Bias	SE-Bias
Res1	0	0	1	0	0
CIHEDO	0,192	0,006	2,164	0,014	0,009
CISYMB	0,182	0,006	1,406	-0,003	0,008
CIMISP	0,157	0,005	1,088	-0,001	0,007
Res3	0,419	0,013	1,867	-0,071	0,019
Res2	0,153	0,005	1,495	-0,009	0,007
Res4	0,182	0,006	1,427	0,025	0,008
Res5	0,19	0,006	1,705	0,003	0,009
Err3	0,073	0,002	0,436	-0,001	0,003
Err2	0,123	0,004	0,597	-0,006	0,006
Err1	0,07	0,002	0,378	-0,01	0,003
Err6	0,094	0,003	0,364	-0,011	0,004
Err5	0,093	0,003	0,385	-0,006	0,004
Err4	0,139	0,004	0,75	-0,005	0,006
Err10	0,112	0,004	0,861	-0,005	0,005
Err11	0,092	0,003	0,403	-0,005	0,004
Err12	0,082	0,003	0,461	-0,005	0,004

Err16	0,449	0,014	0,869	0,079	0,02
Err17	0,543	0,017	2,032	-0,153	0,024
Err18	0,49	0,016	2,518	-0,126	0,022
Err22	0,11	0,003	0,167	0	0,005
Err23	0,25	0,008	2,15	-0,024	0,011
Err24	0,183	0,006	0,703	-0,003	0,008
Err19	0,103	0,003	0,309	-0,009	0,005
Err20	0,066	0,002	0,113	-0,001	0,003
Err21	0,232	0,007	2,142	-0,017	0,01
Err13	0,115	0,004	0,711	-0,012	0,005
Err14	0,1	0,003	0,473	-0,003	0,004
Err15	0,109	0,003	0,532	-0,005	0,005
Err9	0,109	0,003	0,378	0,004	0,005
Err8	0,142	0,004	0,717	-0,019	0,006
Err7	0,131	0,004	1,147	0,002	0,006

Squared Multiple Correlations: (Group number 1 - Default model)

Parameter	SE	SE-SE	Mean	Bias	SE-Bias
OPLEAD	0,045	0,001	0,261	0,001	0,002
OPSEEK	0,032	0,001	0,054	0,004	0,001
INWRIT	0,053	0,002	0,104	-0,005	0,002
INREAD	0,058	0,002	0,43	-0,004	0,003
INRECO	0,061	0,002	0,374	-0,001	0,003
CIMISP01	0,057	0,002	0,486	-0,002	0,003
CIMISP03	0,059	0,002	0,707	0,006	0,003
CIMISP04	0,048	0,002	0,835	-0,003	0,002
OPSEEK05	0,041	0,001	0,801	0,001	0,002
OPSEEK04	0,039	0,001	0,82	0	0,002
OPSEEK01	0,049	0,002	0,689	0,003	0,002
INREAD04	0,063	0,002	0,302	0,007	0,003
INREAD03	0,023	0,001	0,96	0,001	0,001
INREAD01	0,036	0,001	0,89	0,004	0,002
INRECO03	0,061	0,002	0,764	0,001	0,003
INRECO02	0,072	0,002	0,322	0,006	0,003
INRECO01	0,038	0,001	0,942	0	0,002
INWRIT03	0,133	0,004	0,267	0,037	0,006
INWRIT02	0,157	0,005	0,394	0,043	0,007
INWRIT01	0,155	0,005	0,705	-0,028	0,007
OPLEAD06	0,033	0,001	0,815	0,001	0,001
OPLEAD05	0,034	0,001	0,853	0,001	0,002
OPLEAD04	0,05	0,002	0,626	0	0,002
CISYMB01	0,064	0,002	0,652	0	0,003
CISYMB02	0,037	0,001	0,845	0,002	0,002
CISYMB03	0,043	0,001	0,837	0,004	0,002
CIHEDO01	0,029	0,001	0,85	0,003	0,001
CIHEDO02	0,049	0,002	0,763	0,002	0,002
CIHEDO03	0,035	0,001	0,803	-0,001	0,002

Bootstrap Confidence (Group number 1 - Default model)

Bias-corrected percentile method (Group number 1 - Default model)

95% confidence intervals (bias-corrected percentile method)

Scalar Estimates (Group number 1 - Default model)

Regression Weights: (Group number 1 - Default model)

Parameter			Estimate	Lower	Upper	P
OPLEAD	<—	CIHEDO	0,335	0,255	0,417	0,003
OPLEAD	<—	CISYMB	0,238	0,125	0,362	0,002
OPLEAD	<—	Res1	1,035	0,926	1,169	0,002
INWRIT	<—	OPLEAD	0,404	0,047	0,618	0,012
OPSEEK	<—	CIMISP	0,27	0,102	0,468	0,003
INREAD	<—	OPSEEK	0,462	0,284	0,683	0,007
INREAD	<—	INWRIT	0,582	0,442	0,748	0,002
INRECO	<—	INWRIT	0,443	0,257	0,633	0,001
INRECO	<—	INREAD	0,313	0,156	0,476	0,019
CIHEDO03	<—	CIHEDO	0,916	0,842	1,009	0,002
CIHEDO02	<—	CIHEDO	0,947	0,848	1,039	0,004
CIHEDO01	<—	CIHEDO	1	1	1	...
CISYMB03	<—	CISYMB	1,154	1,012	1,322	0,004
CISYMB02	<—	CISYMB	1,222	1,101	1,39	0,004
CISYMB01	<—	CISYMB	1	1	1	...
OPLEAD04	<—	OPLEAD	1	1	1	...
OPLEAD05	<—	OPLEAD	1,271	1,146	1,418	0,004
OPLEAD06	<—	OPLEAD	1,188	1,066	1,328	0,005
INWRIT01	<—	INWRIT	1	1	1	...
INWRIT02	<—	INWRIT	0,736	0,462	1,715	0,003
INWRIT03	<—	INWRIT	0,603	0,332	1,478	0,003

INRECO01	<—	INRECO	1	1	1	...
INRECO02	<—	INRECO	0,607	0,448	0,749	0,005
INRECO03	<—	INRECO	0,915	0,797	0,999	0,008
INREAD01	<—	INREAD	1	1	1	...
INREAD03	<—	INREAD	1,049	0,992	1,108	0,004
INREAD04	<—	INREAD	0,605	0,47	0,725	0,005
OPSEEK01	<—	OPSEEK	1	1	1	...
OPSEEK04	<—	OPSEEK	1,172	1,078	1,285	0,002
OPSEEK05	<—	OPSEEK	1,164	1,05	1,291	0,007
CIMISP04	<—	CIMISP	1,33	1,173	1,562	0,003
CIMISP03	<—	CIMISP	1,257	1,061	1,512	0,005
CIMISP01	<—	CIMISP	1	1	1	...

Standardized Regression Weights: (Group number 1 - Default model)

Parameter			Estimate	Lower	Upper	P
OPLEAD	<—	CIHEDO	0,407	0,313	0,504	0,004
OPLEAD	<—	CISYMB	0,235	0,129	0,336	0,002
OPLEAD	<—	Res1	0,86	0,804	0,906	0,004
INWRIT	<—	OPLEAD	0,329	0,082	0,494	0,008
OPSEEK	<—	CIMISP	0,224	0,084	0,367	0,003
INREAD	<—	OPSEEK	0,369	0,232	0,503	0,009
INREAD	<—	INWRIT	0,545	0,313	0,666	0,002
INRECO	<—	INWRIT	0,396	0,169	0,547	0,002
INRECO	<—	INREAD	0,298	0,148	0,48	0,017
CIHEDO03	<—	CIHEDO	0,897	0,856	0,931	0,004
CIHEDO02	<—	CIHEDO	0,872	0,808	0,922	0,005
CIHEDO01	<—	CIHEDO	0,92	0,879	0,945	0,013
CISYMB03	<—	CISYMB	0,913	0,862	0,956	0,007
CISYMB02	<—	CISYMB	0,918	0,869	0,952	0,007
CISYMB01	<—	CISYMB	0,807	0,715	0,874	0,006
OPLEAD04	<—	OPLEAD	0,791	0,722	0,847	0,005
OPLEAD05	<—	OPLEAD	0,923	0,882	0,955	0,005
OPLEAD06	<—	OPLEAD	0,902	0,863	0,939	0,005
INWRIT01	<—	INWRIT	0,857	0,543	0,947	0,006
INWRIT02	<—	INWRIT	0,592	0,401	0,873	0,005
INWRIT03	<—	INWRIT	0,479	0,281	0,76	0,004
INRECO01	<—	INRECO	0,971	0,93	1,009	0,004
INRECO02	<—	INRECO	0,562	0,431	0,681	0,005
INRECO03	<—	INRECO	0,874	0,786	0,927	0,011
INREAD01	<—	INREAD	0,941	0,893	0,971	0,01
INREAD03	<—	INREAD	0,98	0,952	0,999	0,008
INREAD04	<—	INREAD	0,543	0,415	0,645	0,007
OPSEEK01	<—	OPSEEK	0,829	0,767	0,883	0,007
OPSEEK04	<—	OPSEEK	0,906	0,86	0,947	0,004
OPSEEK05	<—	OPSEEK	0,894	0,843	0,936	0,006
CIMISP04	<—	CIMISP	0,915	0,862	0,962	0,003
CIMISP03	<—	CIMISP	0,837	0,74	0,893	0,009
CIMISP01	<—	CIMISP	0,698	0,607	0,772	0,004

Covariances: (Group number 1 - Default model)

Parameter			Estimate	Lower	Upper	P
CIHEDO	<->	CISYMB	0,354	0,121	0,587	0,005
CIHEDO	<->	CIMISP	-0,198	-0,444	-0,02	0,032
CISYMB	<->	CIMISP	0,259	0,077	0,489	0,004

Correlations: (Group number 1 - Default model)

Parameter			Estimate	Lower	Upper	P
CIHEDO	<->	CISYMB	0,204	0,069	0,331	0,006
CIHEDO	<->	CIMISP	-0,13	-0,268	-0,008	0,042
CISYMB	<->	CIMISP	0,209	0,059	0,374	0,005

Variances: (Group number 1 - Default model)

Parameter	Estimate	Lower	Upper	P
Res1	1	1	1	...
CIHEDO	2,14	1,775	2,544	0,004
CISYMB	1,409	1,055	1,792	0,003
CIMISP	1,089	0,791	1,43	0,003
Res3	1,938	0,873	2,565	0,004
Res2	1,504	1,245	1,822	0,002
Res4	1,402	1,093	1,821	0,006
Res5	1,702	1,311	2,069	0,005
Err3	0,438	0,288	0,572	0,004
Err2	0,603	0,38	0,86	0,003
Err1	0,387	0,272	0,547	0,001
Err6	0,375	0,22	0,579	0,001
Err5	0,391	0,233	0,616	0,002
Err4	0,755	0,538	1,134	0,001

Err10	0,866	0,662	1,112	0,003
Err11	0,408	0,249	0,604	0,002
Err12	0,466	0,305	0,629	0,003
Err16	0,789	0,31	2,094	0,007
Err17	2,185	0,874	2,994	0,002
Err18	2,644	1,468	3,27	0,003
Err22	0,168	-0,047	0,389	0,142
Err23	2,174	1,717	2,689	0,002
Err24	0,706	0,401	1,135	0,002
Err19	0,318	0,158	0,586	0,001
Err20	0,114	0,004	0,265	0,042
Err21	2,16	1,736	2,664	0,002
Err13	0,723	0,521	0,99	0,001
Err14	0,475	0,269	0,674	0,004
Err15	0,537	0,325	0,774	0,003
Err9	0,374	0,175	0,6	0,004
Err8	0,736	0,509	1,099	0,001
Err7	1,144	0,911	1,419	0,004

Squared Multiple Correlations: (Group number 1 - Default model)

Parameter	Estimate	Lower	Upper	P
OPLEAD	0,26	0,18	0,354	0,004
OPSEEK	0,05	0,007	0,135	0,003
INWRIT	0,109	0,007	0,244	0,002
INREAD	0,434	0,305	0,545	0,004
INRECO	0,375	0,245	0,498	0,004
CIMISP01	0,487	0,368	0,596	0,004
CIMISP03	0,7	0,547	0,797	0,009
CIMISP04	0,837	0,744	0,925	0,003
OPSEEK05	0,8	0,711	0,877	0,006
OPSEEK04	0,821	0,739	0,897	0,004
OPSEEK01	0,687	0,589	0,78	0,007
INREAD04	0,295	0,172	0,417	0,007
INREAD03	0,96	0,906	0,998	0,008
INREAD01	0,886	0,797	0,944	0,01
INRECO03	0,764	0,618	0,858	0,011
INRECO02	0,316	0,186	0,464	0,005
INRECO01	0,942	0,866	1,017	0,004
INWRIT03	0,23	0,079	0,578	0,004
INWRIT02	0,35	0,161	0,763	0,005
INWRIT01	0,734	0,295	0,897	0,006
OPLEAD06	0,814	0,745	0,882	0,005
OPLEAD05	0,852	0,777	0,912	0,005
OPLEAD04	0,626	0,521	0,717	0,005
CISYMB01	0,651	0,512	0,763	0,006
CISYMB02	0,843	0,756	0,906	0,007
CISYMB03	0,833	0,743	0,912	0,007
CIHEDO01	0,847	0,773	0,894	0,013
CIHEDO02	0,761	0,653	0,849	0,005
CIHEDO03	0,804	0,733	0,868	0,004

Minimization History (Default model)

Iteration		Negative eigenvalues	Condition #	Smallest eigenvalue	Diameter	F	NTries	Ratio
0	e	16		-0,597	9999	6234,29	0	9999
1	e	17		-0,623	3,188	3480,637	20	0,608
2	e*	7		-0,714	1,059	2213,117	5	1,007
3	e*	6		-0,434	0,226	2007,149	6	0,671
4	e	3		-0,193	0,535	1474,582	6	0,959
5	e	1		-0,057	0,742	1038,612	5	0,832
6	e	0	790,302		0,55	826,036	5	0,762
7	e	0	435,854		0,645	732,035	2	0
8	e	0	400,68		0,35	698,955	1	1,124
9	e	0	413,85		0,117	696,439	1	1,082
10	e	0	406,753		0,024	696,387	1	1,021
11	e	0	406,854		0,001	696,387	1	1,001

Bootstrap (Default model)

Summary of Bootstrap Iterations (Default model)

(Default model)

Iterations	Method 0	Method 1	Method 2
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0

5	0	0	0
6	0	0	1
7	0	0	8
8	0	23	6
9	0	104	1
10	0	121	1
11	0	103	0
12	0	43	0
13	0	25	0
14	0	13	0
15	0	8	0
16	0	4	0
17	0	8	0
18	0	14	0
19	0	17	0
Total	0	483	17

0 bootstrap samples were unused because of a singular covariance matrix.
0 bootstrap samples were unused because a solution was not found.
500 usable bootstrap samples were obtained.

Bootstrap Distributions (Default model)

ML discrepancy (implied vs sample) (Default model)

```
                           -----
                           ------
                 726,214   *
                 766,126   **
                 806,038   ***
                 845,951   *****
                 885,863   *********
                 925,775   ***************
                 965,687   *****************
N = 500          1005,599  ********************
Mean = 991,202   1045,512  **************
S. e. = 4,205    1085,424  *************
                 1125,336  *******
                 1165,248  **
                 1205,161  **
                 1245,073  *
                 1284,985  *
                           -----
                           ------
```

ML discrepancy (implied vs pop) (Default model)

```
                           -----
                           ------
                 750,685   *
                 765,778   **
                 780,871   *****
                 795,964   ************
                 811,057   *****************
                 826,15    ********************
                 841,243   *************
N = 500          856,336   *******
Mean = 830,648   871,428   *****
S. e. = 1,570    886,521   *****
                 901,614   ***
                 916,707   *
                 931,8     *
                 946,893   *
                 961,986   *
                           -----
                           ------
```

K-L overoptimism (unstabilised) (Default model)

```
                           -----
                           ------
                 -625,053  *
                 -479,351  **
                 -333,65   *****
                 -187,948  *********
                 -42,247   ***********
                 103,454   *******************
                 249,156   ********************
N = 500          394,857   *****************
Mean = 275,151   540,559   ************
S. e. = 15,267   686,26    **********
                 831,962   ****
```

```
977,663     ****
1123,364    *
1269,066
1414,767    *
            ______
            _______
```

K-L overoptimism (stabilised) (Default model)

```
                        ______
                        _______
                2,873   *
               45,377   ***
               87,861   *****
              130,384   ************
              172,888   *******************
              215,391   *******************
              257,895   *****************
N = 500       300,398   *******************
Mean = 261,191 342,902  *******************
S. e. = 4,714 385,405   **********
              427,909   *******
              470,413   **
              512,916   **
              555,42    **
              597,923   *
                        ______
                        _______
```

ML discrepancy (implied vs pop) (Default model)

```
                        ______
                        _______
              750,685   *
              765,778   **
              780,871   *****
              795,964   ************
              811,057   *****************
              826,15    *********************
              841,243   *************
N = 500       856,336   ********
Mean = 830,648 871,428  *****
S. e. = 1,570 886,521   *****
              901,614   ***
              916,707   *
              931,8     *
              946,893   *
              961,986   *
                        ______
                        _______
```

Model Fit Summary

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	59	696,387	241	0	2,89
Saturated model	300	0	0		
Independence model	24	6169,763	276	0	22,354

RMR, GFI

Model	RMR	GFI	AGFI	PGFI
Default model	0,289	0,847	0,81	0,681
Saturated model	0	1		
Independence model	0,769	0,335	0,278	0,309

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	0,887	0,871	0,923	0,912	0,923
Saturated model	1		1		1
Independence model	0	0	0	0	0

Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI

Default model	0,873	0,775	0,806
Saturated model	0	0	0
Independence model	1	0	0

NCP

Model	NCP	LO 90	HI 90
Default model	455,387	380,221	538,185
Saturated model	0	0	0
Independence model	5893,763	5641,469	6152,433

FMIN

Model	FMIN	F0	LO 90	HI 90
Default model	2,024	1,324	1,105	1,564
Saturated model	0	0	0	0
Independence model	17,935	17,133	16,4	17,885

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	0,074	0,068	0,081	0
Independence model	0,249	0,244	0,255	0

AIC

Model	AIC	BCC	BIC	CAIC
Default model	814,387	823,634	1041,156	1100,156
Saturated model	600	647,022	1753,063	2053,063
Independence model	6217,763	6221,524	6310,008	6334,008

ECVI

Model	ECVI	LO 90	HI 90	MECVI
Default model	2,367	2,149	2,608	2,394
Saturated model	1,744	1,744	1,744	1,881
Independence model	18,075	17,341	18,827	18,086

HOELTER

Model	HOELTER .05	HOELTER .01
Default model	138	146
Independence model	18	19

Execution time summary

Minimization:	0,031
Miscellaneous:	0,172
Bootstrap:	3,625
Total:	3,828

Appendix B

Survey Items

Item	Question (German)	Question (English)	AUM	AON
RECIRECO	Haben Sie bereits Produktempfehlungen von einem Online-Shop erhalten?	Have you already obtained product-related recommendations from an online shop?	✓	✓
	Wie häufig kaufen Sie folgende Produkte in Online-Shops...	How frequently do you buy the following products in online shops...		
FREQBOOK	Bücher	Books	✓	✓
FREQMUSI	Musik	Music	✓	✓
FREQMOVI	Filme	Movies	✓	✓
IMPUBU01	Beim Einkaufen kaufe ich öfters Dinge, die ich nicht beabsichtigt habe zu kaufen.	When I go shopping, I buy things that I had not intended to purchase.	✓	✓
IMPUBU02	Wenn ich beim Einkaufen etwas sehe, das mich interessiert, kaufe ich es, ohne an die Folgen des Kaufes zu denken.	I am a person who makes unplanned purchases.	✓	
IMPUBU03	Ich bin eine Person, die ungeplante Einkäufe tätigt.	When I see something that really interests me, I buy it without considering the consequences.	✓	✓
IMPUBU04	Es macht mir Spaß, spontan Dinge zu kaufen.	It is fun to buy spontaneously.	✓	✓
IMPUBU05	Ich vermeide es, Dinge zu kaufen, die nicht auf meiner Einkaufsliste stehen.	I avoid buying things that are not on my shopping list.	✓	
TRUSSH01	Einkaufen über das Internet ist unzuverlässig.	Shopping over the Internet is not reliable.	✓	✓
TRUSSH02	Einkaufen über das Internet ist nicht vertrauenswürdig, es gibt zu viele Unsicherheiten.	Shopping over the Internet is not trustworthy, there are too many uncertainties.	✓	✓
TRUSSH03	Man kann sich nicht auf die Versprechen von Verkäufern im Internet verlassen.	One cannot depend on promises given by e–vendors.	✓	✓
TRUSSH04	Die Gefahren des Einkaufens über das Internet werden in der Regel überschätzt.	The risks of shopping over the Internet are generally overrated.	✓	✓
PRIVCO01	Ich bin besorgt, dass meine persönliche Daten, die ich im Internet angebe, missbraucht werden könnten.	I am worried that the personal data I provide on the Internet may be misused.	✓	✓
PRIVCO02	Ich habe die Sorge, dass meine persönlichen Daten, die ich im Internet angebe, in einer Art und Weise benutzt werden können, die ich nicht bedacht habe.	I am concerned that the personal data I provide on the Internet may be used for purposes other than intended.	✓	✓
PRIVCO03	Ich bin über die Angabe meiner persönlichen Daten im Internet besorgt, da ich nicht wissen kann, was Dritte damit anfangen.	I am worried about the personal data I provide on the Internet, because I do not know how third parties handle them.	✓	✓
PRIVCO04	Ich habe keine Bedenken, meine persönlichen Daten im Internet anzugeben.	I have no concerns to provide my personal data on the Internet.	✓	
SKEPAD01	Das Ziel von Werbung ist es, den Kunden zu informieren.	We can depend on getting the truth in most advertising.	✓	
SKEPAD02	Werbung ist im Allgemeinen glaubwürdig.	Advertisings's aim is to inform the consumer.	✓	

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