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Online Information Search with Electronic Agents: Drivers, Impediments, and Privacy Issues

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Based on an online experiment with 206 subjects the thesis investigates how consumers search for high-involvement products online and herein rely on the assistance of electronic advisor agents.

In the context of a camera purchase traditional constructs relevant in offline information search (including perceived product risk, purchase involvement and product knowledge) are tested for their relevance in an online environment. In addition, new constructs impacting online search, namely privacy concerns and flow, are analyzed. Finally, information search behavior for cameras is compared with the one for jackets.

One major finding is that agents do not play the same role in, and are not equally important for, online information search in different product categories. Thus, it appears, that the search process for the experience good 'jacket' involves relatively less reliance on an electronic agent than this is the case in the purchase process for cameras. Moreover, the separate analysis of manually controlled and agent-assisted search shows that, at a significant level, consumers prefer to manually control the search process the more risk they perceive. In line with older studies the data also suggest that the more product knowledge a consumer perceives the less he interacts with an agent for information search purposes.

In the last chapter, the thesis focuses on a potentially major impediment for agent interaction, namely consumer privacy concerns. The empirical results show that, against expectations, privacy concerns to not seem to significantly impede consumer disclosure online. In contrast, evidence is produced that if systems offer appropriate returns in the form of personalized recommendations online users seem to be ready to reveal even highly personal information. The findings suggest that there is a lot of room for online marketers to communicate with their clients through dialogue-based electronic agents. If marketers used the spectrum of legitimate personal questions that are related to the product selection process more systematically, they could gain valuable insight into their customers' decision making process as well as on decisive product attributes. However, unfavorable privacy settings do seem to induce a feeling of discomfort among users which then leads to less interaction time. Marketers therefore have to provide for a comforting privacy environment in order to make their customers feel good about the interaction.

Keywords: Online Information Search, Personal Agents, Electronic Privacy, Perceived Purchase Risk

Informationssuche im Internet mit elektronischen Agenten: Treibende Faktoren, Einsatzbarrieren und die Rolle der Privatsphäre

Basierend auf einem Onlineexperiment mit 206 Teilnehmern untersucht die Dissertation, wie Konsumenten im Internet nach Informationen zu hochwertigen Produkten suchen und welche Rolle dabei virtuelle Verkaufsberater (elektronische Agenten) spielen.

Im Kontext eines online Kamerakaufes mit Hilfe eines virtuellen Agenten wird der Erklärungswert traditioneller Faktoren der Informationssuche für das Onlinemedium untersucht. Dabei werden das wahrgenommene Kaufrisiko, die persönliche Bedeutung des Kaufes sowie das vorhandene Produktwissen als Einflussvariablen getestet. Darüber hinaus wird untersucht, welche Rolle das Datenschutzbewusstsein des Konsumenten in der Interaktion spielt und wie stark ein Zustand des ‚Flows' (fließen) die Informationssuchtiefe beeinflussen. Die für Kameras beobachtete Onlinesuche nach Produktinformationen wird in einem zweiten Schritt mit der Onlinesuche nach Jacken verglichen.

Eine wesentliche Erkenntnis der empirischen Arbeit ist, dass virtuelle Verkaufsberater bei der Suche nach unterschiedlichen Produkten nicht dieselbe Wichtigkeit haben. So wird deutlich, dass sich Konsumenten auf der Suche nach dem Erfahrungsgut Jacke relativ weniger auf die Empfehlung des Agenten verlassen als dies im Kaufprozess von Kameras der Fall ist. Hinzu kommen einige signifikante Anzeichen dafür, dass Konsumenten den Suchprozess stärker zu kontrollieren wünschen und weniger an Agenten delegieren, desto mehr Kaufrisiko bzw. Kaufunsicherheit sie empfinden. Schließlich zeigt sich analog zu älteren Studien, dass Konsumenten mit mehr Produktwissen weniger mit virtuellen Verkaufsberatern interagieren.

Im letzten Kapitel der Dissertation geht es um eine potentiell maßgebliche Barriere für den Einsatz von virtuellen Verkaufsberatern: die Angst von Konsumenten ihre Privatsphäre einzubüßen und zum ‚gläsernen Kunden' zu werden. Die empirischen

Ergebnisse legen hier jedoch nahe, dass Datenschutzbedenken die Konsumenten nicht davon abhalten, sich online mitzuteilen. Ganz im Gegenteil wird deutlich, dass Konsumenten sogar bereit sind, sehr persönliche Informationen von sich preiszugeben, wenn das System eine entsprechende Gegenleistung bietet (wie beispielsweise eine persönliche Produktempfehlung). Die Ergebnisse suggerieren, dass es einen großen Gestaltungsspielraum für Unternehme gibt, über elektronische Dialogsysteme mit ihren Kunden zu kommunizieren. Würden Unternehmen das potentielle Spektrum an persönlichen Fragen nutzen, die im Rahmen eines Kaufprozesses sinnvoll sind, könnten sie wertvolle Einblicke in das Entscheidungsverhalten ihrer Kunden gewinnen. Hingegen sollte beachtet werden, dass eine mangelhafte Berücksichtigung des Datenschutzes gleichzeitig auch Unbehangen beim Nutzer auslöst, welches sich in signifikant kürzeren Interaktionszeiten wiederspiegelt. Es ist daher im Interesse von Unternehmen, für eine datenschutzfreundliche Interaktionsumgebung zu sorgen.

Schlagworte: Informationssuche, Persönliche Agenten, Datenschutz, Kaufrisiko

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Chapter 1

1 Introduction

The dramatic growth of the Internet as an electronic shopping and commerce environment for both B2C and B2B transactions has led to a strong research interest into the effects of this new electronic medium on economic relationships.

Current revenues from European B2C retail markets, which form the research frame for this thesis, are estimated to account for around € 19 billion. And this number is expected to grow quickly to € 174 billion by 2005 [Nordan, 2000].

One major driver for this expected growth is the increasing deployment of automated tools, including *electronic agents*, that assist users in the buying process. While today's online shopping is mostly a 'user-driven' task that offers only limited interaction and confronts consumers with the tedious problem of information overload, electronic consumer agents are promising to deliver a whole new way of purchasing goods and services. Practitioners and academics alike expect this to ring in a 'second-generation' of electronic commerce [Pazgal, 1999; Vulcan, 1999]. In this scenario, many of the consumer's decision-making tasks are delegated to, or at least assisted by, virtual assistants. These have access to a myriad of information sources and are able to filter them according to user preferences [Alba et al., 1997]. Eventually, these agents may even negotiate purchase conditions on behalf of users [Maes et al., 1998; Preist, 1998].

Against the background of these anticipated developments, this thesis focuses on the deployment of agent technology from a marketing perspective. The goal in doing so is to study potential drivers and impediments for the further acceptance and use of electronic agents in consumer markets.

1.1 Electronic Consumer Agents in Marketing Research

The study of human-agent interaction, from a marketing perspective, was probably initiated by Alba et al. in 1997, who investigated the theoretical implications of agent assisted search for consumers, retailers and manufacturers. This group of academics argued that the informational advantages provided by electronic consumer agents would have the potential to reduce buyer search cost and optimize decision making, but also outlined some main criteria on which the growth of interactive home shopping with agents would depend (like reliability of information sources and access to a vast selection of products).

Based on these theoretical reflections empirical research was conducted to test some of the hypotheses made. Häubl and Trifts [2000], for example, showed how recommendation agents are able to effectively reduce consumers' search effort for product information, augment the quality of the consideration set as well as of the final purchase decision. Pederson [2000] presented similar work showing how consumer agents are able to optimize the information search part of the buying process and partially enhance consumer choice. Brynjolfsson and Smith [2000] investigated the effect of 'shopbot' use on price sensitivity and found that brands and retailer reputation have a significant effect to obtain price advantages.

All of these research projects studied agents with a view to their role as facilitators in information search. Yet, little attention has been paid to the fact that many different *agent roles* can be distinguished, offering different types of benefits to consumers and reaching beyond the support of information search.

One group of marketing academics who distinguished agent roles were West et al. [2000]. They showed that agents can act as tutors, clerks, advisors and bankers for consumers. While tutor-agents educate clients about the features available in a product category and help them uncover preferences, clerk-agents focus on assisting their clients in complex information search processes and product screening. Advisor agents may be called upon to express expert opinions on products and are able to provide tailored advice. Banker-agents are envisioned to negotiate purchases on consumers' behalf and facilitate the purchase of products and services.

Despite this existing distinction of agent roles in electronic commerce, there has been little research on design challenges or economic effects that these different roles entail. In contrast, academics tend to use the general term ‘agent’ or ‘shopbot’ when they actually refer to clerk or advisor agents. And as a result, it seems as if a more systematic exploration of the technology in its different facets has so far been widely ignored.[1]

In order to correspond to this lack of ‘role–recognition’ in consumer–agent marketing research, chapter 2 of this thesis starts out with a detailed analysis of West et al.’s framework [2000] on agent roles, and proposes an extension for it, relating these roles to different purchase situations. This extension is then used to argue that agent acceptance is particularly challenging when it comes to the deployment of the technology in high-involvement purchase situations.

When agents are used to support high-involvement purchase decisions, one major challenge for the technology is to win consumers’ trust [West et al., 2000; Urban et al., 1999]. An empirical study that has explicitly investigated this issue is the one presented by Urban et al. [1999]. The group of academics tested the acceptance of a trust-based *advisor-agent*[2] for the truck market and found that only half of those subjects who indicated to like buying online really preferred an agent-based site for product search. A clear preference was found among all subjects for Web sites that offer not only an agent system, but also manually accessible, “information intensive” shopping sites.

Thus, there was a need detected among users to manually control at least parts of the information flow. Consumers who then expressed a preference for using an advisor-agent were those who were not very knowledgeable about vans, younger and more

[1] For example, no marketing research has been done on the effects of automatic recommender systems (tutor-agents) on decision making, an agent type amongst the widest ones used in electronic commerce today.

[2] The concept of advisor agent will be presented below. It refers to agents that give tailored advice to consumers, mostly in ‘high-involvement’ purchase situations.

frequent Internet users. They also had visited more van dealers in advance of a real-world shopping trip.

Urban et al.'s research shows that agent advice is not always the most preferred solution for all consumers. In addition, it suggests that there are drivers and impediments such as product knowledge or demographics that influence the degree to which agents are accepted. Given this first empirical evidence, chapters 4 and 5 of this thesis explore such drivers and impediments in more detail. A number of factors derived from information search literature are investigated that are hypothesized to motivate or impede users' reliance on agents. The frame to do so is similar to Urban et al.'s in that interactions between consumers and an advisor-agent are studied for a high-involvement purchase context. In a next step, one particular impediment for agent interaction and trust in the system is then studied in more detail: online consumers' privacy concerns.

Urban et al. [1998 cited in West et al., 2000], in fact, suggested that privacy is one major trust building cue when consumers interact with agents. Many household surveys indirectly support this view, reporting strong privacy concerns of online users [Pew Internet & American Life Project, 2000; Ackerman et al., 1999; Westin, 1996]. In many cases, these concerns even lead to false data provisions [Grimm et al., 2000; Sheehan and Hoy, 1999]. Consequently, a number of agent researchers have pointed at privacy concerns as a major challenge for agent acceptance [Shearin and Maes, 2000; West et al., 2000, Norman, 1994].

Acknowledging the significance of privacy concerns as an impediment to human–agent interaction, chapter 6 of this thesis focuses on the issue in more detail.

1.2 Thesis Structure

To study consumer interactions with agents, chapter 2 starts out with a general introduction outlining what electronic consumer agents actually are. A definition of the agent concept is included to avoid the widespread misconception of the term [Franklin and Graessner, 1996] and make clear what type of technology and application is referred to in the rest of the thesis. Then, potential agent roles in electronic commerce are discussed and it is argued how these different roles gain relevance for different types of purchase situations. Most importantly, it is shown that agent acceptance by consumers is particularly challenging when these software tools are used to support high-involvement, targeted search.

Targeted search with consumer agents, and especially with dialogue-based systems, requires considerable effort on the part of the user [West et al., 2000]. In order to comprehend what drives and impedes consumers in high-involvement situations to use or avoid agents, an experiment has been conducted with over 200 subjects in the form of a 'real-world' online shopping trip. This experiment and the results obtained are presented in chapters 3 to 6 of the thesis. While chapter 3 gives a detailed overview of the experiment, chapters 4 to 6 report on the findings made. Chapter 4 presents a structural equation model. It tests potential drivers and impediments for consumers to rely on agent-based and/or manually controlled search forms in a high-involvement purchase situation. The results obtained in this analysis help to nail down some concrete factors that influence consumers' interaction readiness and reliance on agent technology.

Chapter 5 then looks in more detail into how consumer interactions differ when they shop for two different product categories online. Here, again, a focus is being put on the two main search forms available: agent-based versus manually controlled search. Finally, chapter 6 focuses on one particular and potential impediment to consumer interaction with agents: privacy concerns. The chapter contains the elaboration of a model that captures personal consumer information cost, a measure for the negative utility attached to the revelation of personal information to electronic agents. Based on this measure (and other variables), the degree of disclosure practiced by experimental participants during the shopping session is investigated. In a next step, the degree of disclosure is compared with subjects' proclaimed attitude towards online privacy.

Chapter 7 closes with major conclusions that can be drawn from the empirical work and suggestions for future research.

Chapter 2

2 Agent Roles and Challenges in Electronic Commerce

2.1 What is an agent anyway? [3]

The *intelligent agent* is a concept that has been around for more than 25 years. Even so, the definition of the term 'agent' has seen a lot of debate [Franklin and Graessner, 1996]. The main reason for this debate is that the term 'agent' is so appealing that many academics and journalists like to use it, fuelling "…*ancient dreams of true intelligent assistants"* [Foner, 1993, p.40]. As a result, the term agent has been used to describe technologies from simple macros in which the user enters a few parameters to truly intelligent assistants which demonstrate learning ability and artificial intelligence.

In response to this watering-down of the electronic agent concept, the research community has at various times attempted to define a number of central elements constituting an electronic agent [Franklin and Graessner, 1996, Gilbert et al., 1995 cited in Vulcan, 1999; Foner, 1993]. Foner [1993] proposed that defining traits of an agent are its autonomy, its capacity to personalize and its ability to have a discourse with the user. *Autonomy* refers to the fact that an agent can pursue an agenda independently of its user, which requires some aspects of periodic action, spontaneous execution and incentive. *Personalizability* implies that the agent can adapt its interactions to the specific needs, preferences and goals of the user, eventually relying on a user model. *Discourse* finally relates to the concept of interactivity between a user and his agent: *"a two-way feedback, in which both parties make their intentions and abilities known, and mutually agree on something resembling a contract…"* [p.35].

[3] This section heading is derived from an influential paper on personal agents with the same title [Foner, 1993].

Given these characteristics, Foner refers to the concept of the *personal agent* (PA) and therefore puts emphasis on the human–machine interaction. While PAs are the focus of the current thesis, it must, however, be mentioned that agent technology is also being actively researched with a view to building *multi-agent systems* (MAS). Here, the exchange between two or more artificial agents is examined (for example, the exchange of information between agents on electronic markets).[4] As a result, the definition of what agents are is somewhat broader than Foner initially proposed. Researchers at IBM, for example, developed a framework in 1995 that defines the scope of intelligent agents on three dimensions (see figure 1): agency, mobility and intelligence [Gilbert et al., 1995]. While *agency* respects the aspect of discourse with the user, it also integrates the idea that agent interactions must not be limited to a human-machine dialogue, but could also refer to an exchange between artificial agents (e.g. in order to negotiate prices). The *intelligence* construct is similar to what Foner called 'personalizability', but respects that not everything an agent has learned must be related to the user. Intelligence means that an agent is capable to interpret, learn and improve. And finally, *mobility* is the degree to which agents themselves travel through the network, i.e. in order to interrogate remote host sites for product information.

[4] Note that the research distinction between PAs and MASs is well recognized in the research community and demonstrates itself, for example, in the organization of different conferences on multi-agent systems (International Conference on the Practical Application of Intelligent Agents and Multi-Agent Technology (PAAM) and personal agents (International Conference on Autonomous Agents (AA)).

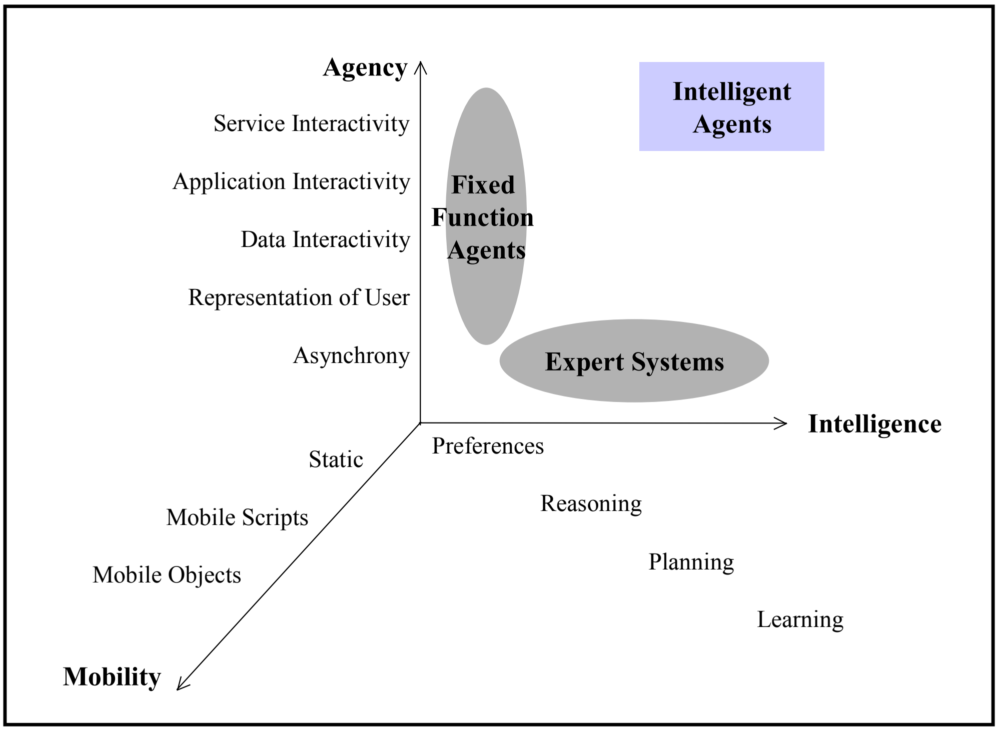

Abbildung 1: Scope of Intelligent Agents as defined by Gilbert et al. [1995]

2.2 Currently Employed Versions of Personal Agents in Consumer Markets

PAs currently employed in electronic commerce and various software applications support different user tasks including: information filtering, information retrieval, mail management, application usage or online shopping. For shopping agents, a distinction is again being made between agents involved in merchant brokering (finding the best suited vendor) and product brokering (finding the best suited product) [Maes et al., 1999]. In this thesis a focus is being put on PAs supporting product search and evaluation.

Given the definition of 'agent', systems which are currently deployed supporting product search and evaluation (namely recommender systems, shopbots and interactive decision guides), integrate a number of the agent properties introduced above. Recommender systems are used by online vendors to suggest products to their customers [Schafer et al., 1999]. Recommendations are usually based on customer knowledge accumulated by the system over time, or that has been communicated during a session by the user (e.g. through an interactive discourse). While an increasing number of commercial websites start to integrate interactive functionalities [Dysart, 1998], many recommender systems can also be described as *"automatic"* [Schafer et al., 1999, p.162]. Automatic recommender systems are those that do not need any explicit effort by a customer in order to generate the recommendation. Recommendations made are usually personalized, respecting either the type of product sought by a customer or by referring to the user in person. An often-cited example for such a recommender system is the 'Customer Who Bought' feature employed by Amazon.com[5] which recommends books that are related by title, author, or place of purchase. Considering these characteristics of current recommender systems, it becomes clear that they possess many agent properties. However, they also have one major drawback: usually they are only capable to recommend products that are for sale within the domain in which they are operated. Consequently, product recommendations are based only on a limited selection of what is available on the market.

Shopping agents in contrast search the entire Web (or at least large parts it) for product details and mostly make price comparisons or recommend products based on a limited number of user's preferences [Palmer and McVeagh, 2000]. Well-established examples of this type of agent include MySimon.com[6] or DealTime[7]. However, while these applications use other (remote) domains to collect product information and also display some forms of agency through their interactive functionalities (product attributes usually have to be specified by the user), shopping bots are to date not very 'intelligent'. They are only capable of searching on the basis of very few user preferences, typically the price, and they are not able to learn.

Interactive decision guides, in contrast, are much more sophisticated in the detection of user preferences. Examples for this type of product brokering agent include PersonaLogic[8] or Active Buyer's Guide[9]. In contrast to product configuration

[5] see also (on 10.01.02) www.amazon.com

[6] see also (on 10.01.02) www.mysimon.com

[7] see also (on 10.01.02) www.dealtime.com

[8] PersonaLogic has been bought by AOL since this thesis was started. Insights into the type of interaction offered by PersonaLogic is available from (on 10.01.02): http://pattie.www.media.mit.edu/people/pattie/ECOM/sld018.htm

engines which can be found on manufacturer sites such as Dell.com or Apple.com, these interactive decision guides are utility-based, which means that through an extensive discourse with the user they try to identify the most suitable products (on the basis of a user's personal preferences).[10] Based on market research data or directly specified utilities, they then determine the relative importance of different user specifications.

As recommender systems, shopbots and interactive decision guides display a number of agent characteristics, they will be considered hereafter as early stage forms of PAs. [11]

2.3 Roles for Agents in Commerce, and Related Design Challenges

2.3.1 Agents in Different Roles: A Discussion of West et al.'s [2000] Framework

It was argued above that little attention has been paid to the distinction of roles agents can play for consumers. This distinction is, however, important, because it allows one to systematically infer technical challenges and potential impediments of agent use that these systems have to overcome in order to be accepted by consumers.

The first attempt to systematically distinguish different types of agents from a marketing perspective and to investigate corresponding design challenges has been made by West et al. [2000]. The group of academics differentiated agents that take a tutor, clerk, advisor or banker role according to the decision making task they support in different parts of the purchase process (see figure 2).

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[9] see also (on 10.01.02) www3.activebuyersguide.com/start.cfm

[10] Note that product configuration machines on vendor Web sites only correspond to the 'direct manipulation' by users; a product is constructed from its different parts, but there is no 'agency' involved in this activity.

[11] Some scholars who defend a *strong personal agent hypothesis* would not agree that some shopping bot applications or interactive decision guides cited here are agents. These academics (e.g. [Maes, 1994; Liebermann, 1997] argue that agents must be able to learn ("watch over a user's shoulder") and must be able to act autonomously upon a user model. However, this is not an uncontested view [Nwana and Ndmum, 1999]. It is not adopted by this thesis.

Consumer Tasks in the Buying Process	**Preference Construction & Discovery**	**Information & Alternative Search**	**Product Evaluation**	**Purchase**
Agent Roles	***Tutor:*** *Educate about product featurs, uncover preferences*	***Clerk:*** *Assist in information search & product screening*	***Advisor:*** *Express expert opinion, provide tailored advice*	***Banker:*** *Negotiate on client's behalf, facilitate purchase*
Key Challenges for Agent Acceptance				
Improve Decision Quality	Preference Detection	Information Filtering	Learning	-
Increase Consumer Satisfaction	Interface Design Control over Personalization and Data Use Managing User Expectations			
Develop User Trust	Overcoming User Privacy Concerns Transparancy of Agent's Method Perception of User Control			

Abbildung 2: Agent Roles in the Purchase Process as Proposed by West et al. [2000][12]

When agents take the role of a tutor, they aim to help construct user preferences, uncover needs and make the consumer discover new products. Important for this type of agent is that it does not annoy customers with information they are not interested in. As a result, this type of agent has to be particularly capable of detecting user interests and preferences. When an agent takes the role of a clerk, consumers already know broadly what product they seek. The clerk's role is thus less to uncover preferences or point out objects of interest, but to assist clients in performing the tedious task of searching for information and product screening. The challenge for this type of agent is that it has to have access to a myriad of databases and has to be able to retrieve and filter data in such a way that consumers' preferences are respected. Advancing from a customer clerk to be a true customer advisor places even more emphasis on the agent's capability to understand and match customer preferences. When advisor agents help customers to evaluate products, they have to have a well refined user model (that includes user utilities for product attributes) and

[12] Please note that this figure only gives a summary of the main subjects raised by West et al. [2000].

access to a corresponding source of rich information. Moreover, advisors should know their clients, implying that this type of agent has to incorporate some learning ability. Finally, when agents serve consumers as bankers, negotiating deals on their behalf, users probably have the highest expectation on agent reliability. Users have to trust that agents match different preferences and negotiation strategies in line with their expectations and also manage well the degree of information revelation about user preferences (e.g. price sensitivity).

The summary of West et al.'s agent framework raises awareness for the fact that user interaction with consumer agents is not a given and that many challenges have yet to be overcome in order to motivate consumers to use the electronic decision aids. It also shows that the technology bears very distinct opportunities to support consumers in different purchasing tasks.

West et al. derive their framework from overall models of the consumer buying process [Howard and Sheth, 1969; Engel et al., 1993]. The more advanced a consumer is in the buying process, the more does he usually know about the product he seeks and is able to challenge agent advice. As a result, agent support must become more sophisticated in order to become acceptable to the consumer.

In addition to rising technical challenges and increasing agent sophistication for different roles, West et al. also mention a number of more 'user-centric' barriers for agent use. These include, among others, management of user expectations, trust and control issues as well as the management of privacy concerns. However, unlike those more technical challenges described above, the authors do not systematically link user-centric design aspects to the different agent roles identified. For example, when it comes to the development of user trust in agent systems, the authors mention the general necessity for agent systems to overcome users' privacy concerns and to constitute the belief that the agent is capable to act and will act in the customer's best interest. For this purpose they see the transparency of an agent's method and the perception of user control as central elements for system design. Yet, as the next sections will show, this reasoning can be refined. Different agent roles also imply different user expectations on and personal investment in the system. Thinking, for example, of an agent that serves as a tutor and raises a customer's awareness for a new type of cereal that has just been introduced to the market. Does that customer really wish to know how and why the agent came up with the suggestion? Is it necessary for this type of tutor agent to give clients a feeling of control? Will the consumer at all be interested to expend the effort to learn about the agent's functioning in this type of context? The example shows that general recipes to improve consumers' acceptance of agents are problematic. In addition, it hints at another dimension that seems to be relevant when discussing agent design challenges and agent acceptance: the purchase context.

Consumer agents are usually built for and deployed to support users in very concrete shopping tasks. However, consumers' personal involvement in shopping tasks differs [Kotler, 1994; Beatty and Smith, 1987] and so may expectations on, and challenges for, agents that support these tasks. Purchase involvement can be described as *"a person's perceived relevance of the object based on inherent needs, values and interests"* [Zaichkowsky, 1985, p.341]. Based on the involvement concept, it will be argued below that many of the challenges discussed for agent acceptance really should be seen more systematically in the purchase context and the agent's role in that context.

Building on West et al.'s [2000] framework it will be proposed how purchase context and related customer involvement could be linked to different agent roles. To do so, insights from studies in consumer behavior are used in which different types of purchases have been distinguished. In addition, it is taken into account that depending on the agent's role and context of its use, consumers may prefer one or the other form of system input and input related effort. Most importantly, it will be discussed to what extent challenges for agent acceptance are relevant with respect to different agent roles.

The banker role of agents will be excluded from further analysis hereafter, because the body of this thesis is more concerned with the process of information search by consumers and less so with financial transactions and negotiation of terms.

2.3.2 Agent Roles and Challenges in Different Purchase Situations

2.3.2.1 Differentiation of Purchase Types and Information Search Behavior in Consumer Markets

To establish a link between agent roles and different types of purchase contexts it seems sensible to use insights from consumer behavior research where different types of purchases have been distinguished. The best-known distinction of products into convenience, shopping and specialty goods is based on the insight that consumers have different shopping habits and expand different degrees of search effort for different kinds of products [Murphy and Enis, 1986; Bucklin, 1963; Copeland, 1923]. While *convenience goods* require the least effort, because consumers usually purchase them frequently or immediately (e.g. tobacco, newspapers, sweets), *shopping goods* mostly lead consumers to actively search for specific product information. (e.g. clothing, furniture, hi-fi equipment). *Specialty goods* (mostly luxury products) imply the highest degree of purchase effort, but less so in order to accumulate product information or compare brands. Instead, 'long ways' such as going out to the Mercedes Benz dealer or making a test drive are considered as the search effort. In the framework elaborated in this section, specialty goods will be not be considered since the true benefit of electronic agents can not unfold in these purchase environments.

Related to the type of product sought is the amount of *active external* information search prior to a purchase [Kotler, 1994; Murphy and Enis, 1986]. This search activity can be *impulsive, habitual or targeted* (see [Kroeber-Riel and Weinberg, 1999 p.244] for an overview).[13] For example, buying sweets, a convenience good, near the check-out counter of a supermarket is a typical impulsive type of purchase and there is usually little search activity involved. Also habitual buying behavior, such as the purchase of salt or other commodities involves little information search effort by consumers. Thus, when it comes to low-cost, frequently purchased products

[13] There is also internal search for information which relates to information stored in memory or passive types of information search where one receives an information e.g. by chance. These types of search are not referred to in this current context though, because agents are seen here as to support only active types of search.

there is evidence that consumers have low-involvement and, as a result, do not extensively search for information about brands, evaluate their characteristics, or make weighty decisions on what product to buy [Kotler, 1994]. Some marketing scholars who look into the modeling of information search behavior in consumer markets [Moorthy et al., 1997] would argue that the perceived benefits from information search for this type of low-involvement good do not outweigh the cost incurred by the search activity.

In contrast to impulsive or habitual purchase environments, many products lead consumers to enroll in targeted and more extensive search activity. These products, which trigger customer search effort, are often subsumed under the term 'shopping goods' [Murphy and Enis, 1986; Copeland, 1923]. *"Shopping goods are those for which the consumer desires to compare prices, quality, and style at the time of purchase"* [Copeland, 1923, p.283]. Thus, buyers are willing to spend a significant amount of time and money in searching for and evaluating these products. Shopping goods can be divided into homogeneous and heterogeneous goods. Homogeneous shopping goods such as books or CDs are seen by consumers as similar in quality but different enough in price. As a result they mostly trigger information search in the form of price comparison shopping [Kotler, 1994]. When shopping for heterogeneous products, in contrast, price is not the primary purchase criterion. Here products such as furniture, clothing, special foods or household appliances are meant for which other purchase characteristics such as personal taste, fashion or performance play a role in addition to price.

Relating these different types of purchase tasks and respective information search activity to agent technology raises two questions: First, what type of agent role might be the best suited one to support each type of purchase? And second, how should this role be 'played' by the agent, meaning what type of front-end technology and input system seems to be the most suitable in the respective buying context given customers' different degrees of effort in information search? Before discussing these questions in more detail, a short overview must be given on current front-end systems, which entail different degrees of input effort.

2.3.2.2 *Front-end Agent Systems: A Brief Overview*

For the discussion of front-end technology or input systems for electronic consumer agents, a framework presented by Schafer et al. [1999] can be called upon, which was developed for recommender systems, but may be transferred also to other interface agents. With respect to the amount of user effort that is needed to calculate a recommendation, the authors distinguish four types of input systems [Schafer et al., 1999, p.164]: agents that build their advice on organic navigation, upon the request for a recommendation list, on selected options or on keyword (freeform) specifications.

Recommendations made by systems on the basis of *organic navigation* require the least amount of user effort, because they are deducted from what the system observes about a user or the objects he is interested in. For instance, if a customer has placed a few items in his shopping basked, the system may recommend complementary products to increase the order size (based on 'item-to-item correlations'). Recommendations can also come in the form of average ratings or a list of other customers' comments or choices. For example, the Customer Comments functionality in Amazon.com's website allows customers to view the ratings and text reviews that other customers provided. In each of these applications, recommendations appear automatically as part of the item information page and do not demand any active client input.

Recommendation lists do not require much more work from customers either. Here, users only request system recommendations once, for instance by subscribing to a newsletter on specific offers, or product categories they are interested in. When marketers (website hosts) have new products to offer or other information of interest to the consumer then this information is automatically sent out to him. An alternative to this e-mail type of information provision is that a user actively requests a recommendation from the system. The system in this case uses former transactions of this user (e.g. purchases made or ratings given) and compares these with those of other users. Based on what the customer's 'nearest neighbour' liked or purchased the system then provides recommendations (often employing so called *collaborative filtering techniques* [Shardanand and Maes, 1995]). The Book Matcher functionality integrated in Amazon.com's website is a typical example for this type of front-end technology.

In contrast to systems based on organic navigation or "nearest neighbour" techniques, recommendations based on *selected options* require relatively more interaction willingness from consumers. Typically, customers choose from a set of predefined criteria upon which the system then generates a response. The number of criteria specified can be of very different size. Shopping bots, for example, require few selected options. As was mentioned above, they usually search for products only on the basis of price and product category information. In contrast, when a user interacts with an interactive decision guide, such as Active Buyer's Guide, he specifies many more (normally > 20) criteria, including desired product attributes and weighs.

Finally, *keyword or freeform systems* require the most interaction from users. Here, customers have to provide a set of textual keywords upon which the recommendation is then retrieved. In the most advanced system environments, customers can even 'chat' with an anthropomorphic agent on their product wishes and expectations and, ideally, this agent then reacts similarly to a human sales agent, responding to expressed preferences and consulting the customer on best-suited product alternatives. An example for this type of anthropomorphic agent would be Atira,[14] the virtual sales assistant at shopping24.com's website or the agent Marc who sells eye-tracking equipment for Olympus.[15]

2.3.2.3 Agent Roles and Systems in Different Purchase Contexts

Returning to the question what type of agent role and input system may be the most suited in the context of different purchase tasks, it can be argued that consumers' willingness to invest time and effort in the purchase process must have an impact on the type of front-end system employed. Thus, if a consumer does not want to spend time searching for a good he will probably be just as reluctant to actively and extensively interact with an agent to find that good. The degree of input a user is

[14] See also (on 10.01.02): http://www.shopping24.de

[15] See also (on 10.01.02): http://www.eye-trek.de/mobil_e.html

willing to provide then, in turn, influences the role an agent can play. Figure 3 gives an overview of how different types of purchase tasks or different product categories can be related to input systems.

Looking at impulsive or habitual purchases of convenience goods, it has been shown that consumers do not invest much effort and time in order to prepare purchase task [Kotler, 1994]. As a result, agents supporting this task should probably not rely too much on users' input. In contrast, automatic recommendations based on the observation of customers' navigation patterns may be well suited in this type of context. If a consumer has requested specific types of recommendations (e.g. raising awareness to discounts), then an agent could also automatically add this type of information to the shopping environment or notify customers via e-mail. The regular nature of habitual buying seems to ideally lend itself to the use of applications that, in fact, 'look over the shoulder of a client' [Maes, 1994] while, at the same time, it questions the heavy use of selected options or keyword based systems.

Product Context	Convenience Goods	Shopping Goods
Type of Search Ideally Supported by Agent Role	Impulse/HabitualInformati on Search	Targeted Information Search
System Input	Organic navigation, (Recommendation List)	Selected Options, Freeform/Keyword
		Consumer Search Effort & Expected Benefits ↑
Agent Role	Tutor	Clerk, Advisor
Examples*	• Customer who Bought (Amazon) • Customer Comments	• MySimon • PriceWatch • PersonaLogic • Active Buyer's Guide
Challenges for Agent Acceptance	• Preference detection • Learning	• Management of user expectations •Perception of user control •Transparancy of agent's method •Privacy

Abbildung 3: Agent Roles Related to Different Purchase Contexts

The agent role that seems to best fit in this type of context is the one of a tutor. Even though customers mostly know what they want to buy (be it out of habit or impulsively), a tutor agent can raise awareness for new features available in a category that is frequently bought. For example, an agent that has been able to track a customer's preferences could spontaneously suggest products that are either impulsively appealing to the consumer (e.g. "Don't forget the chocolate!" for consumers who like to buy chocolates) or raise awareness for new products in line with the consumer's regular shopping habits (e.g. new low-fat chocolate for somebody who regularly buys low-fat products). At the same time, using clerk or advisor agents in this type of context seems less sensible. Clerk agents that are supposed to assist users in information and alternative search confront the problem that consumers have been shown to search relatively seldom for information when they are purchasing convenience goods [Kotler, 1994]. The impulsiveness and regularity of the purchase task therefore questions the need for a clerk agent. The same is true for an advisor agent. Expert opinion and tailored advice seem to be of less relevance within this type of repetitive and low-involvement purchase context.

When consumers enroll in a more targeted search for shopping goods, it has been shown that they invest more time and effort into the information search process [Kroeber-Riel and Weinberg, 1999]. As a result, agent systems employed in this type of product context can probably rely more heavily on user input than is the case for convenience goods. Selection based or freeform types of front-end systems could therefore be employed. It also makes sense to employ systems where customers can specify product search criteria, because shopping goods are usually chosen on the basis of criteria such as suitability, quality, price and style that are unique and specific to a customer [Kotler, 1999]. Assuming that customers have an idea about many of their preferences, the most reliable form to match client needs with a recommendation is to explicitly ask for preferences.

When consumers search for shopping goods they have to identify relevant product features, set their preferences and then compare products on this basis. This activity was shown to put high demands on consumers' information processing ability [Bettman, 1979], leading in physical markets often to a limited (and economically sub-optimal) amount of external information search prior to purchase [Duncan and Olshavsky, 1982]. Advisor agents such as PersonaLogic or Active Buyer's Guide offer an ideal electronic support to assist consumers in complex purchase decision-making tasks of this type. With the help of an interactive dialogue-system, consumers can be made aware of relevant product features. Preferences and weights can be specified and are automatically considered by the system. Comparison of selected products is then facilitated by product listings. If an advisor agent allowed for price sorting, and integrated a considerable number of vendors it would also automatically embrace the functionality of a clerk agent.

The discussion shows that different purchase tasks call for a specific type of agent role and front-end technology. Consumers welcome different types of electronic support in line with their purchase goals and readiness to invest search effort into the system. As a result, tutor agents basing recommendations on observation of organic navigation will probably be the most welcomed form of agent support in an impulsive or habitual buying process. In contrast, when consumers search in a targeted manner for shopping goods, the availability of clerk or advisor agents may be appreciated.

Certainly, the link between agent technology and purchase task could be investigated in much more detail. The arguments in this section are generic and must be empirically scrutinized. However, such an analysis is not the focus of this thesis. For the current context, it is sufficient to note that the agent's context of use calls for different roles and front-end systems. Based on this argument, challenges for agent acceptance can be discussed more systematically in the next section.

2.3.2.4 Challenges for Agent Acceptance in Different Purchase Contexts

When discussing challenges for agent acceptance in this section, against the background of different agent roles and purchase tasks, the underlying argument is that consumers make cost-benefit tradeoffs when they search for information online. It has been argued by researchers in information theory [Stigler, 1961] and marketing [Moorthy et al., 1997; Dowling and Staelin, 1994] that consumers weigh the cost of searching for information with respective benefits. Assuming that they do the same in online environments, it can be argued that low-involvement interactions with tutor agents imply less demands on electronic agents, because the consumer invests little effort in the system (which is automatic) and consequently expects less benefits. In contrast, when consumers actively search with the help of agents for a high-involvement shopping good, expected benefits are higher and thus put emphasis on the agent's performance.

In their framework, West et al. [2000] state that the general goals of electronic agents are to improve consumer decision quality, to increase satisfaction and to develop trust in the agent. In order to meet these overall goals they then infer a number of equally general design challenges (see again figure 2). The authors argue that in order to increase consumer satisfaction the process of interaction with an agent must appeal to the user, which emphasizes the development of appropriate user interfaces. In addition, the user should have control over the personalization process and use of his personal data. Also, management of user expectations is deemed important, as users might lose faith in a system unless its limits are clearly communicated up front. When it comes to the development of user trust the authors show the necessity for the system to overcome users' privacy concerns and to constitute the belief that the agent is capable to act and will act in the customer's best interest. For this purpose they see the transparency of an agent's method and the perception of user control as central elements for system design. Yet, it is questionable whether all these challenges for agent acceptance are equally important for impulsive and regular shopping tasks as they are for targeted search activities.

Looking, for example, into the purchase process for a convenience good that is supported by a tutor agent. Tutor agents make suggestions to customers, but they do not make recommendations. Do consumers wish to control agent suggestions? After all, 'understanding' the system in this type of context would probably demand more information processing effort from the customer than the entire purchase itself. In contrast, when consumers invest time and information into the search process with an advisor agent for a high-involvement good, they expect benefits from the search in the form of a reliable recommendation. One can evaluate the recommendation's reliability via the transparency of the agent's method; answers to questions such as what and how many data sources the agent uses, how timely, and how independent these sources are. If this information is given, it can also help to manage consumers' expectations of a system. However, again, they might not be required in low-involvement situations. These brief arguments show that user control and trust issues are not equally important for different types of agents, and that more demands exist for systems used in high-involvement purchase situations.

Also when it comes to a user's control of his data, different agent roles and systems may evoke different levels of concern. Extensive online search for shopping goods can imply that consumers enter into a lengthy exchange with an agent system. This exchange can take the form of a freeform interaction with an agent, or the selection of a myriad of options in an interactive decision guide. When consumers enter into these rather lengthy forms of exchange with electronic systems and provide direct information about themselves, exhibiting many of their personal preferences and utilities, it must be explained how this information is being used and dealt with by the hosting site. Given that many civil rights organizations and privacy-conscious users already feel a privacy threat in leaving behind simpler forms of click-stream traces, extensive agent exchange carries an even stronger risk to undermine online consumers' privacy. As a result, privacy is particularly threatened when agents start to communicate with people.

The arguments presented on control and privacy issues show that agent design challenges and potential impediments for their use cannot be discussed in general, but must be considered relative to the specific task and role the agent is supposed to fulfill for the consumer. This is because it is the task that determines a consumer's readiness to invest effort and time into the agent's activity. As Nwana and Ndumu pointed out [1999, p.9]: *"There seems to us to be an issue here – that of the interplay between the nature of the task and the modeling or learning required [by the agent]."*

In addition, the arguments show that challenges for agent acceptance are particularly high when consumers turn to more complex and dialogue-intensive advisor agents. Given this evidence, the body of this thesis exclusively focuses on the investigation of consumers' interactions with advisor agents in high-involvement situations. Here, special emphasis will be put on users' desire to control the search process as well as on the way users deal with their privacy concerns.

Chapter 3

3 Empirical Work

3.1 Overview

In order to investigate consumers' targeted online information search behavior for high-involvement goods an experiment has been carried out in winter 2000 at Humboldt University Berlin. The experiment was designed as an ordinary shopping trip to an experimental online store where participants could shop either for a winter jacket or for a compact camera. 206 subjects were observed through registration of log-file data in their search behavior. Besides manually controlled information zones, the shopping trip was supported by a selected options-based anthropomorphic advisor agent.

The total sample of 206 was split into the two buyer groups. In addition, two different types of privacy regulations (type 1 and type 2) were employed in the store offering shoppers more or less comfort with data handling policies. As a result of these different buying conditions (product and privacy regulation), four treatments summarized in table 1 can be discerned for the empirical research.[16]

[16] In fact, there have been two more empirical treatments, the results of which are not reported extensively in this thesis. They involved the display of brands (vs. no brands for the current sample) and the availability of a physical channel for product inspection (vs. no channel existence for the current sample).

Tabelle 1 Overview of Experimental Treatments:

Treatment No.	Product sought	Privacy Statement confronted	Number of observations made for treatment
1	Camera	Type 1	60
2	Camera	Type 2	92
3	Jacket	Type 1	28
4	Jacket	Type 2	26

The first goal of this analysis(conducted on the basis of experimental data) was to gain insights into the drivers of, and impediments faced by online information search. In particular, when combined with electronic advisor agents. Would interaction levels with an agent be explicable by the same factors as manual driven search? What is the relative importance of agent-based versus manually driven search? In order to investigate these questions, a structural equation model of online information search has been developed and observations from camera-treatments 1 and 2 were used to test it (analysis 1, table 2). The dependant variables in this model were agent-based search and user driven search.

The main reason why only data from camera shoppers have been included in this analysis is that information search behavior was shown to differ between product groups [Kotler, 1994]. And even though compact cameras and winter jackets were similar in value for the experiment, they represent two very distinct types of goods: While jackets entail relatively strong characteristics of an experience good, meaning that consumers like to judge on product quality through feeling and touching different models, cameras display stronger search-good characteristics, meaning that consumption benefits can be predicted more reliably prior to purchase on the basis of factual product information (for the distinction of goods see [Nelson, 1970]). As a result, cameras represent a product class for which the Internet offers relatively strong information advantages. It therefore seemed advisable to not intermingle behavioral findings for this product class with the observations made for jackets (treatments 3 and 4). Restrictions in the size of the dataset for jackets (only 54 observations) prevented a separate calculation and test of the equation model for this product category.

In order to still take account of the impact of product nature on interaction, a second round of analysis was conducted including data from all treatments, camera and jacket shoppers (analysis 2). Leaving behind the more macro-level type of behavioral analysis inherent in structural equation modeling, the information search process for cameras and jackets was analyzed in more detail. For this purpose, the dependent information search constructs, agent-based search and manually controlled search (measured in the equation model on the basis of time and page requests) were pulled apart to smaller pieces of search activity (such as the number of photo enlargements made by a subject). Then the impact of product nature on this micro-level type of search activity was analyzed.

Besides the investigation of 'high level' relationships relevant in online information search, one potential impediment for interaction with agents has been investigated in more detail. This was the privacy concern of online consumers. Privacy concerns turned out to be the most important impediment for agent interaction in the structural equation model. As was mentioned above, they have also been proclaimed as an important factor for agent acceptance [Shearin and Maes, 2000; Norman, 1994]. Investigating privacy issues in agent interactions, the first step was to capture the phenomenon of privacy concern in a regression model. An index was developed that aims to capture personal consumer information cost (PCIC) (analysis 3). Based on this index (as well as other variables), expressed privacy preferences were then compared with actual interaction behavior (analysis 4) during the shopping session.
Table 2 gives an overview of the different analyses made and the number of observations used to make them. All of them will be reported on in more detail in the following chapters of this thesis. The following sections of this chapter will give a more detailed insight into how the experiment was conducted.

Tabelle 2 Overview of Empirical Analysis Made:

Analyses	Results reported in	Treatments included	N° of Observations used to make analysis
1. Structural Equation Model of Online Information Search	Chapter 4	1 and 2	152
2. Product Nature and Online Information Search	Chapter 5	1, 2, 3, 4	206
3. Regression Model of Privacy Concerns	Chapter 6	Separate study	39
4. Privacy Concerns and Actual Behavior	Chapter 6	1, 2, 3, 4	206

3.2 Incentive Scheme and Briefing

The experiment was advertised at Humboldt University Berlin. Its goal was described as a test of user interaction with a highly innovative and high performance product search engine developed for online shopping systems at the Institute of Information Systems at Humboldt University. Students were told that the system would be tested on the basis of a 'real-world' shopping trip for cameras and winter jackets. If people were interested to buy a camera or winter jacket they were asked to sign up for one of the shopping sessions taking place from a computer laboratory at a pre-arranged time.

A major challenge in winning participants for the experiments was to find people with a true interest in one of the two products. As was discussed in section 1.1., the use of money or class credits are a questionable incentive structure when interaction with and reliance on agents is being tested. Participants' interest in the product was assured by making them pay for products out of their own pocket if they wished to buy something. The main incentive to purchase (and participate) was a 60% discount on all products on offer in the store. Unfortunately, project finances were constrained could not offer this discount to all buyers. The incentive structure therefore had to be refined such that a lottery, after shopping, decided (on the basis of one out of ten participants in a lab session) who would have the right to take a product for the 60% off. The remaining participants had the choice to still buy the product for the full price displayed and received a small financial compensation of 20 DM (approximately $ 10) to reward them for their efforts. If someone decided to not buy anything in the online store, but won the lottery, he or she would leave empty. With this incentive scheme in place the desire to purchase was realistic. .Due to the high value nature of cameras and jackets, buyers had to expect, with a relatively high chance of 1:10, to incur a minimum expenditure of 80 DM (approximately $ 40). Participants were made even more aware that they had to pay for purchases by have to sign obligation to pay forms prior to shopping. People who may have come to only cash in the compensation without buying anything were discouraged by the fact that with the same 1:10 chance they would have to bank on leaving empty. In addition to the discount, participants were also promised a personal feedback on their interaction behavior.

Winning experimental participants by offering a product discount and feedback on behavior led to a random self-selection process for all treatments. 92,7% of total participants were students from different university faculties while the remaining 7,3% held different jobs. 55,8% were male and 44,2% female. 98,5 % of the participants indicated to have experience with the Internet and 91,7% of them would even regularly use it (for SPSS output file see Appendix D, table D1). With these user traits in the data the advantage is that a relatively well-educated cross-section of the population with considerable online experience has been observed. Online behavior cannot be attributed to the 'naivety' of subjects in interacting with the online system. Also, a relatively prominent target segment for today's electronic commerce environments has been investigated: 56,3% of the participants indicated that they had already bought something online. Given these demographics and the characteristics of the participants, a disadvantage of the experiments is that the sample is not representative of the German population or consumers in general. In addition, only those people that are relatively open to use direct marketing channels such as the Internet, (and are thus ready to handle the risk of not being able to touch and feel the product before buying) may have registered for the experiments.

When the term ‘consumer’ or ‘Internet user’ is employed in the following sections to comment on observed behavior, then this generalization is made only to facilitate the description of relationship and reading of the thesis. The ‘student’ as a particular type of consumer observed and referred to should be kept in mind by the reader.

3.3 Materials and Apparatus

The central material for the experiment was an online store with two different versions, one offering compact cameras and the other one offering winter jackets (for screenshots see Appendix B1). In addition to this online part of the experiment, a battery of questions was answered by participants before and after the shopping session which was identical for jacket and camera shoppers (Appendix A5). The shop’s functioning was tested twice before the experiment took place. The first tested the enhanced store design and layout, and the second the performance of the recommendation algorithm.

3.3.1 Navigation Opportunities in the Experimental Online Store

The experimental online store was programmed explicitly for the experiment, using Meta-HTML and Java. In order to encourage product search, the shop had a vast range of models on sale including 48 compact camera models and 100 winter jackets (50 models displayed to women and 50 to men). The reason why there were so many different models on offer for each product was that the agent was intended to be highly responsive to users’ expressed product preferences, making the benefits of interaction visible for participants. At the same time, participants were let to feel slightly overwhelmed by the volume of alternatives giving them an incentive to invest themselves into the search process.

The interactive opportunities participants encountered in the store were similar to those in website like ActiveBuyersGuide.com or PersonalLogic.com. The online store’s starting page had been loaded into the Web browser by the experimenters when the participants arrived at the lab. It displayed either a camera or a jacket storefront depending on the product the subject had registered for. In the store navigation was organized in three phases: When participants entered the online store they had a space for orientation (phase 1) where they had the possibility to view all products on offer, one by one, from a list. From there, users proceeded to the agent domain where an anthropomorphic 3-D advisor agent ("Luci") enrolled the user in a communication or interaction phase (phase 2). The interaction offered 56 purchase related agent questions and was organized into 7 cycles of 7-10 questions that a user could run through with the agent. The 7 question cycles were displayed to the user on a category survey page leaving him the choice to run through the agent questions in any order he preferred and to the depth he deemed necessary. Within each question cycle it was ensured that with the help of a 'dialogue control box' (situated on the upper left part of the screen) users would be aware of the questions still to come in a question cycle and control for the questions already answered or skipped. Users were not forced to provide any answers. At the bottom of answer options to each question there was one graphically separated option entitled as 'no answer'. Based on any number of multiple-choice answers provided by the participating shopper, Luci could be asked to calculate a Top-10 ranking of products.[17] From this ranking list, customers could then view a more detailed description of each product and enlarge its photograph (phase 3). The detailed product description contained a brief marketing text on the respective model displayed, the enlargeable photograph and a fact sheet summarizing major product attributes for each alternative. This phase closely resembled the current user driven style of electronic commerce environment. Appendix B1a gives an overview of the navigational phases the experimental participants encountered.

In the analyses presented hereafter, the communication phase with agent Luci and her recommendations will be considered as representative for agent-based information search, while participants' inspection of product details represents a typical form of manual search. With the three shopping phases orientation, dialogue and detailed product inspection, navigation resembled an offline store visit. The shopping process could be exited at any time and a purchasing decision could be made after the request for a product information page (in phase 3).

[17] Prior to shopping, subjects were told that if they did not wish to communicate with the agent at all the ranking of products would be in random order.

3.3.2 Store Manipulation

An important condition under which real-world online shopping takes place is that users' demographic identification data is often known to the host of a web site. Websites such as that of the infomediary Yahoo!.com[18], for example, offer users the possibility to register with the domain. As a result, navigational behavior can be attributed to a person and online marketers are enabled to create personal profiles of their customers. As was discussed, many studies have revealed that privacy concerns of users oppose these practices. In order to create the same type of privacy-sensitive environment two manipulations were integrated in the store: First, agent Luci addressed a user with his or her first name, using the data that had been collected from candidates during registration. And second, participants were given the opportunity to provide their home address. Thus, after phase 1 where participants viewed all products one by one from a list, and just before phase 2, a html-page appeared on which shopping agent Luci introduced herself and her purpose to the user. All users had to pass this page and were given the possibility to leave their home address with the agent. No reason was given on this page why a user should do so, but two 'proceed'-buttons were displayed on the bottom of the page: one labelled "save address, proceed" and the second right below entitled 'no address specification, proceed'. The user was left to decide whether to reveal the address or not without any sanctions.

Finally, another condition was integrated in the online store aiming to ensure extensive information search: no brand information was displayed on any of the products or product descriptions. The reason for this manipulation was that brand names were shown to serve as *information chunks* for consumers [Jacoby and Hoyer, 1981; Weinberg, 1981]. *"Information chunks are information particularly relevant for the judgment of products and that are able to substitute or bundle a number of other information"* [Kroeber-Riel and Weinberg, 1999, p.280]. By avoiding brand names, it was ensured that all participants navigated under the same conditions and that superior levels of brand knowledge of some participants would not lead to uncontrollable 'short-cuts' by some subjects in identifying the right product.

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[18] See also (on 10.01.02): www.yahoo.com

3.3.3 Identical Store Design for Compact Cameras and Winter Jackets

In order to conduct analysis 2 (see table 2) it was vital to design the two store versions for cameras and winter jackets as similarly as possible so that differences in navigational behavior could be attributed to product nature and not to the store environment. The store therefore offered identical navigational opportunities and product display in its two versions including a similar quantity of products on offer, a similar number of attributes used to describe each product and an identical breadth of agent communication.

In addition, a considerable effort was made to provide for a similar perception of the agent dialogue in the two store versions. For this purpose, interaction was characterized and manipulated on three dimensions: First, the satisfaction with agent communication would have to be perceived as similar as possible for the two store versions. This put emphasis on the search algorithm used in the two stores (for a description of the algorithm used see Appendix B2). Secondly, the degree to which the agent dialogue would be perceived legitimate and important needed to be similar, in order to have people interact with the two store versions on the same premises. And finally, the way in which communication was organized in the store had to be the same as order effects have been shown to impact online navigation [Hoque and Lohse, 1999]. More detail on how identical store perception was ensured is commented on in section 5.1.2.

3.3.4 Development of Agent and Agent Dialogue

Abbildung 4: Image of Sales Agent Luci

Agent Luci deployed in the experiment as a female sales assistant was a selected option-based dialogue system. She was represented as a 3-D anthropomorphic and moving image (see figure 4). The reason why such a human-like interface agent was integrated into the system was that it was shown that visually personifying the interface (e.g. through a computer animated face) can lead to general social facilitation [Sproull et al., 1996].

In addition to this sociable side of the agent, the image was also used to draw users attention to specific details on pages, such as the permanent option to call for the Top-10 Ranking of products. The moving facial image was licensed from the company Artificial Life.[19]

Agent Luci offered consumers a catalogue of 56 questions to comment on purchase-related needs. Most of these questions were developed with the help of human sales agents selling compact cameras and winter jackets in a premium department store in Berlin. All of them were somehow linked to the purchase context, but many of them went beyond simple product attribute specification and also addressed 'softer' purchase concerns. The reason why softer sales aspects were integrated in the interactive system was to observe how far users would go in the revelation of personal information as a part of the information search process. Interest in users' marginal willingness to reveal information was also the reason why users were offered so many agent questions to answer. Seen that successful sales conversations in offline environments involve in average 3,3 questions answered to a sales agent [Haas, 2001], it was expected that the 56 agent questions integrated in the online sales dialogue would not be fully exhausted by most of the shoppers.

On the basis of group discussions among the researchers involved in IWA[20] all agent questions were characterized on two dimensions: First, each agent question was assigned to one purchase risk that it would primarily help to address, being either of functional, financial, social or psychological nature.[21] Second, each agent question was characterized as to the degree in which it would address the online user in person and thus intrude more or less in his or her privacy. Four privacy classes were

[19] (on 10.01.02) http://www.artificial-life.com
[20] See acknowledgments

distinguished for this purpose: 1*) non-private questions* addressing specific attributes sought in the product (e.g.: How resistant do you want the fabric of the jacket to be?), 2*) marginally private questions* that referred to the consumer in person, but were also closely linked to product choice (e.g.: How important is the resistance of the fabric of jackets to you?) 3) *relatively private questions* looking into the usage envisaged with the product (e.g.: Where do you want to wear the jacket?) and 4) *purely private questions* that would somehow be related to the sales context, but be completely irrelevant for product choice. (e.g.: Where do you obtain your knowledge about fashion? in the purchase context for jackets). Appendix B3 gives a detailed overview of all agent questions as well as their respective assignments to risk and privacy classes. Here, more detail is also provided on the rules set to formulate questions and assign them to the classes in an identical manner (Appendices B4 and B5).

Finally, all agent questions were tested in an independent and separate study. Based on the judgment of 39 subjects (see table 2), they were rated as to their perceived legitimacy and importance in an Internet sales context. In addition, the difficulty and willingness to answer them in an online sales context were respected. Mean ratings are summarized in Appendix B3.

3.3.5 Pre and Post-Shopping Questionnaires

Before and after the shopping trip, all participants were asked to fill out a paper-and-pencil questionnaire which was identical for both camera and jacket shoppers. Questionnaire data was used to measure independent variables potentially explaining the behavior observed during the online shopping sessions. Most questions used were taken from earlier studies in information search and other literature sources. The pre-shopping questionnaire (see Appendix A5a) addressed demographics, budget constraints [Dowling and Staelin, 1994; Moore and Lehmann, 1980], self-confidence [Kiel and Layton, 1981], information consciousness [Punj and Staelin, 1983], Internet experience and e-privacy concerns [Ackerman et al., 1999] as well as product perception. Measurement of product perception included product knowledge [Srinivasan and Ratchford, 1991; Kiel and Layton, 1981], product experience [Punj and Staelin, 1983; Kiel and Layton, 1981; Moore and Lehmann, 1980], perceived

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[21] For more detail on the concept of perceived risk, see section 4.2.1.

product risk prior to purchase [Bettman, 1975 and 1973; Cunningham, 1967] as well as perceived uncertainty to judge product quality [Weiber and Adler, 1995a]. After the shopping session, participants were asked to comment on the perception of the sales agent, encountered purchase risk, motivation to shop [Jacoby et al., 1978], perception of flow variables [Csikszentmihaly and Csikszentmihaly, 1995], ability to recognize brands by the product form as well as perceived legitimacy and importance of agent questions (analogues to the independent study mentioned above) (see Appendix A5b).

3.4 Procedure

When subjects arrived at the laboratory it was first ensured that everyone had a good understanding of the incentive scheme. In preparation that a subject might purchase (and win the lottery), everybody was asked to sign and hand in a Consent of Payment (Appendix A2) document. The Consent of Payment was necessary as the experiment organizers did not offer credit card facilities and also had no postal distribution service integrated in the online service. The Consent of Payment further supported the aim of raising participants' awareness of online purchasing consequences. Then, participants sat down and filled out the first questionnaire. When they handed in this first battery of questions they simultaneously received a paper-based privacy statement (Appendices A3a and A3b) what would explain data handling policies of the experimental online store as well as a description of the navigational opportunities in the store (Appendix A4). The privacy statement surprised participants with the information that log-files would not only be used for research purposes, but also handed on to a 3rd party, that did not wish to be named for the time being. Two different types of privacy statements were used: In the 'soft' privacy statement (type 1), participants were told that an industrial sponsor, a reputable European company, would receive all navigational data. Also, their rights according to the EU Directive 95/46/EC were stated in this privacy statement, including the right to know who makes use of the data, to view them and if necessary change or withdraw them. In the 'harsh' privacy statement (type 2), participants were told that their data would be handed on to an anonymous entity, and that it was not known what further use would be made of their data. Before entering the store, participants were required to sign this privacy statement and hand it in to the experimenters.

After all questionnaires and privacy statements had been handed back to the experimenters, a briefing was read out aloud to the group and final questions were answered (Appendix A1). The briefing contained information on the further experimental process and hints to the organization of navigation in the store as well as agent performance. In addition, the privacy regulation signed was further commented on, telling participants that it would not be in the interest of the experimenters ”to collect dummy data”. They would therefore be expected to give truthful answers, because the search engine would not work adequately otherwise. It was added that the experimenters would ”prefer a refusal to answer a question from an agent, than a lie”. After all, participants were given “the explicit opportunity to not answer agent questions”. The way this privacy briefing was formulated and read out aloud to the subjects, one goal was to minimize sympathy , or ‘warmth’ with the experimenters. The reason for this was that laboratory environments tend to make subjects feel ‘secure’ and behave more trustworthy than they would naturally do in a real-world context, the so called ‘Hawthorne effect’ [Mayo, 1933]. Generally, the goal of the privacy statement was to create a navigational context similar to the Internet where data is collected not only by the host server of a visited service, but also by third party servers (i.e. advertising companies).

Finally, people were asked to take their time shopping and not rush through the store remaining for at least 30 minutes in the laboratory. In order not to adversely affect the feedback of their performance, however, they were also told to remain no longer than necessary in the store, and to leave it once they felt shopping was completed. Employing this time-manipulated set-up some of the influence of time cost that is usually present when people surf and buy online was avoided [Hoque and Lohse, 1999]. This was done consciously, because if people had been given freedom in time there would have been many users with different personal time agendas leading to uncontrollable earlier break-ups. The aim was to avoid this, for in the current study it was more important to control model variables than to observe the absolute time investment users make to decide on a purchase.[22]

[22] Other studies that are based on conventional log-file analysis can do so much more effectively.

Once participants had received the verbal briefing, they started out for the online shopping trip. When they had finished they gave a sign to the experimenters who provided them with the post-shopping questionnaire. Once this questionnaire was filled out, participants left the lab. Outside the lab, the lottery and compensation occurred as well as verbal debriefing discussions with the participants. The whole process took about 1,5 hours per session in which ten participants were involved at a time.

3.5 Benefits and Drawbacks of the Empirical Research

In contrast to earlier studies in information search (in offline markets) the empirical findings of this study do not rely on self-reported activities, but are based on actual behavior observed. As a result, our empirical research does not suffer from selected-memory effects; consumers recalling only parts of their behavior which they can remember [Kroeber-Riel and Weinberg, 1999].

Another benefit of the empirical study conducted is that a 'pure' and instantaneous impact from different behavioral constructs on information search could be observed. External effects such as branding could be excluded. Through questionnaire data it was possible to explain behavior. A study based on log-file data from a real-world website only would have made the collection of questionnaires difficult. In addition, information search would have been impacted by the fact that product brands are displayed and that pages are loaded with a vast range of distracting content.

By using a sophisticated electronic advisor agent it was possible to win insights into people's dealings with this emerging type of technology and its relative importance in the information search process in comparison to today's user driven consultation of detailed product descriptions.

At the same time, the complexity of the experimental set-up implies a number of disadvantages. First, in comparison to psychological studies in consumer behavior the current experiment leaves room for many variables going unobserved. For example, some participants might have intuitively liked the image of shopping agent

Luci more than others. This perception of visualization may then have impacted behavior. Second, it was impossible to control for all pre-dispositions of participants. Perhaps some really came only for the 20 DM compensation and were ready to take a 1:10 chance to leave empty. Others may have really come to buy a product. As there are limits to what one can measure as influential factors there are limits to the explanatory power of the observations made. Finally, the sample size was limited to only 206 which is a very small basis to reliably interpret behavior in the way this was done with Structural Equation Modeling presented below.

Chapter 4

4 Online Information Search for High Involvement Goods: A Structural Equation Modelling Approach

4.1 User Control in High-Involvement Online Searches with Agents

When consumers pursue targeted search online today, they do not chiefly rely on agents. Instead, most of the product search conducted on the Web is still done manually by visiting different Web sites, investigating product listings, descriptions or photographs. Some consumers do both, search manually and with the help of an agent when they shop online.

One main difference between manual information search and agent-based search is that in the former case the user *"manually initiates and directly controls"* the information search process [Pazgal, 1999, p.1] while in the latter case he delegates a considerable part of the search responsibility to the autonomous software system. Thus, while the user-driven type of product search implies that consumers *control the selection process* from the total spectrum of available product offerings to a reduced consideration set, agent search implies that this act of selection is done automatically. As a result, the consumer loses control over a considerable part of the search process while at the same time saving effort due to task delegation. As was discussed above, this loss of control is a major challenge for agent acceptance and it is therefore regarded as a central aspect in human-agent interaction [Norman, 1994].

However, the discussion of user control reaches beyond concrete agent design issues. It is also at the centre of a debate on whether agents are at all sensible to use at the interface level [Shneiderman and Maes, 1997]. Shneiderman who is sceptical of using agents in the interface and instead proposes search that is *directly manipulated* by the user states: *"The philosophical contrast is with 'user-control, responsibility, and accomplishment'. Designers who emphasize a direct manipulation style believe that users have a strong desire to be in control and to gain mastery over the system…Historical evidence suggests that users seek comprehensive and predictable* *systems and shy away from complex unpredictable behavior…"* [Shneiderman, 1997, p.36]. In contrast, agent proponents, even though they recognize the importance of user control and understanding, see a necessity in agent technology in order to *"reduce work and information overload*" [Maes, 1994, p.1]. They argue that by 'making the user model available to the user' (e.g. with the help of comprehensive interfaces) sufficient control and understanding is achieved. Furthermore, they argue control may be sacrificed for other benefits such as time savings. As Maes states: *"I don't mind giving up some control, actually, and giving up control over the details as long as the job is done in a more-or-less satisfactory way, and it saves me a lot of time"* [Shneiderman and Maes, 1997, p.54].

A key problem when it comes to agent-assisted targeted product search is that a consumer does not know for a long period of time whether the search process has been done in a 'more-or-less satisfactory way'. Unlike for example an agent-based mail filtering system where a user can immediately check whether the agent has correctly sorted and filtered incoming messages, the quality and reliability of a consumer shopping agent can, to its full extent, only be judged upon at the moment the recommended product has been received or even tried out. Of course, it can be argued that the online consumer already regains search control once the agent has presented a consideration set, which he can then carefully examine before purchasing anything. Certainly, agent designers can also integrate control points into the systems; i.e. information on whether the agent was able to find independent product reviews or search reputation networks allowing users to decide whether the search has proceeded in a satisfactory way. However, as Widing and Talarzyk [1993] have pointed out, there is some risk that the selection of products made by agents could be sub-optimal for consumers[23] and there are certainly limits to what can be communicated to consumers for control purposes. As a result, consumers who actively search for products and explicitly order an agent to conduct part of the product search for them always have to *trust* the system to a certain extent, sacrificing some of their control. In future agent scenarios, where some academics envision software systems that take over the entire purchase process without referring back to the user [Borking et al., 1999; Pazgal, 1999], this problem of trust

[23] Widing and Talarzyk [1993] showed that using attribute cut-offs to screen alternatives tends to result in inferior product decisions due to inadvertent product elimination.

and control will be even more serious. It is not surprising therefore that Urban et al. recognized in 1998 that the final and arguably most important requirement of a successful agent would be that it develops and maintains trust [Urban et al., 1998]. To the extend that consumers, however, do not develop trust in agents, they will probably continue to rely on manually controlled search forms or prefer directly manipulateable interfaces. The question is on what factors this trust in or reliance on an agent finally depends.

As was mentioned above, Urban et al.'s [1999] study on the acceptance of a trust-based advisor agent produced some first insights into the conditions under which consumers are prepared to delegate tasks to agents. The degree of product knowledge a customer has on the product he seeks, his age and Internet experience were shown to be relevant drivers for agent use. Given this evidence, this thesis chapter raises the question whether there are not other user and context specific factors that can explain the degree of reliance on and information search with advisor agents.

For this purpose, user-controlled, manual search activity and agent-based search are investigated and compared as to their drivers and impediments. Gained insights are deducted into factors that explain some of consumers' wish for more or less control in a targeted information search process online.

The factors used to investigate targeted online information search are derived mainly from studies in offline information search behavior. These studies have discussed a myriad of potential drivers and impediments to impact and explain consumer search behavior (see [Beatty and Smith, 1987, p 86] for an overview). For example, it was found that besides product knowledge and experience [Punj and Staelin, 1983; Kiel and Layton, 1981] there are also factors such as perceived product risk [Sundaram and Taylor, 1998; Dowling and Staelin, 1994; Srinivasan and Ratchford, 1991; Capon and Burke, 1983] and purchase involvement [Sundaram and Taylor, 1998; Beatty and Smith, 1987] that determine depth and breadth of information search. Personal variables related to search have not been restricted to age [Katona and Mueller, 1955 cited by Beatty and Smith, 1987], but were also found in the form of attitude towards search [Thorelli and Thorelli 1997; Punj and Staelin, 1983], education [Claxton et al., 1974] or self-confidence [Kiel and Layton, 1981].

Investigating the influence of some of these traditional concepts on targeted online information search a structural equation model is presented below. The dependant variables in this model are manually controlled, user-driven information search and agent-based search. And as all potentially explanatory factors for behavior are tested separately for the two constructs, insights are being gained into what drives and impedes users to rely more or less strongly on an advisor agent instead of personally controlling information sources. Figure 5 gives an overview of the model tested. The next section reports on the concrete hypotheses integrated in it.

4.2 Model Constructs and Hypotheses

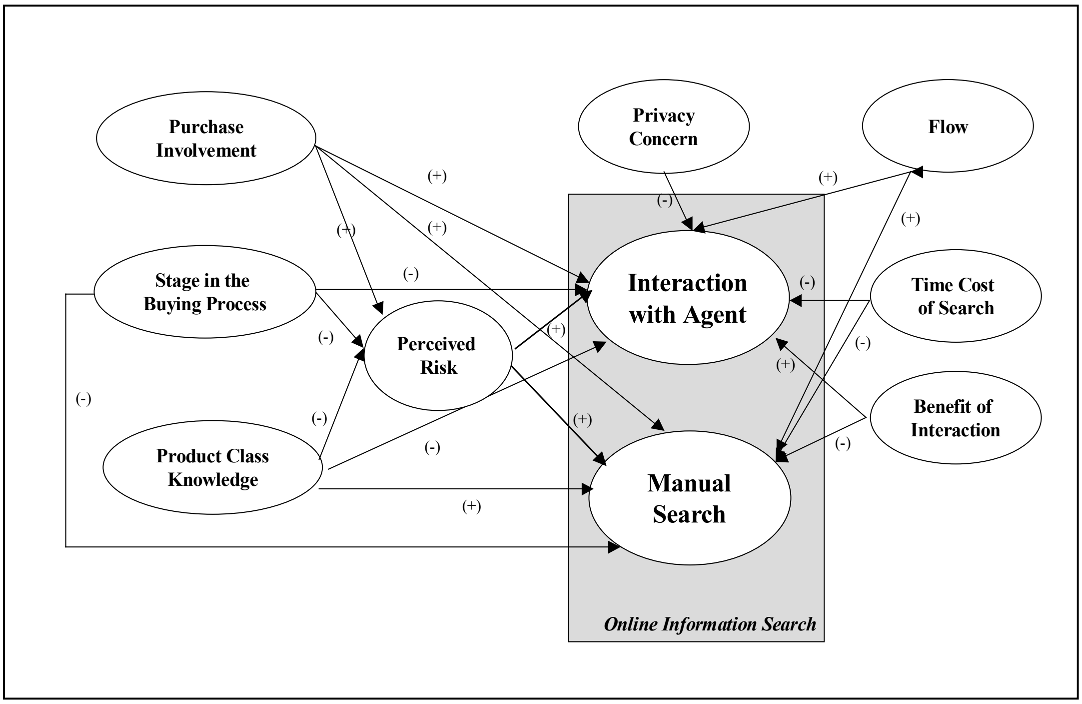


Abbildung 5: Model of Online Information Search: Unobserved Constructs and Stated Directionality of Relationships

4.2.1 Endogenous Model Constructs

At the core of the structural equation model is the dependant construct of online information search. In line with the distinction between agent assisted and manually controlled search these two forms of online search are also distinguished for the current model. A number of drivers and impediments have been hypothesized to explain them.

One construct frequently investigated in the context of information search is *perceived risk*. Perceived product risk denotes a consumer's assessment of the consequences of making a purchase mistake, as well as of the probability of such a mistake occurring [Cunningham, 1967]. As a result of this initial risk assessment consumers were shown to engage in information search in order to reduce the perceived risk to an acceptable level. More precisely, risk was shown to be a multidimensional construct with consumers differentiating between functional, financial, social and psychological risk [Kaplan et al., 1974]. Functional risk is the uncertainty that a product may not perform as expected, financial risk that the product will not be worth the financial price and would have been available cheaper elsewhere, socio-psychological risk that a poor product choice will harm the consumer's ego or may result in embarrassment before one's friends, family or work group.

Probably, most risk dimensions relevant in the physical purchase process will continue to play a role in online environments. However, it could be that the degree to which individual risks are perceived is different online than offline. For example, as the online medium allows for much greater price transparency it may be that the financial risk of buying overpriced products is relatively low compared to little transparent offline markets. At the same time, being not able to touch and really see the product anymore, the socio-psychological risk might be higher in online markets than for their offline counterpart. In addition, there might be a new dimension of risk gaining relevance online, which is the delivery risk attached to a purchase. Buyers might fear that products won't arrive on time or be in perfect condition. Because there was no delivery service included in the experimental store, delivery risk has not been included in the current model.

The influence of perceived purchase risk on information search has been investigated in a myriad of studies [Dowling and Staelin, 1994; Srinivasan and Ratchford, 1991; Kaplan et al., 1974; Cox, 1967]. Also for in-home shopping environments its relevance has been confirmed [Sundaram and Taylor, 1998]. In his meta-analysis of the risk construct Gemünden [1985] concludes, however, that perceived risk seems to be particularly valid for high-involvement goods and less so for commodities, because lower levels of product risk do not trigger information search as a risk reduction strategy. As a result of these findings, perceived risk has been included in our model of online information search. It was expected that higher levels of perceived risk would lead participants to use both means of search in a relatively intensive manner. As former models of information search have suggested a mediating role of risk between exogenous variables such as product knowledge and information search [Srinivasan and Ratchford, 1991], perceived risk was considered as an endogenous variable in our model and it was hypothesized that:

H1: The more product risk a consumer perceives prior to the purchase of a camera, the more he or she will interact with an electronic advisor agent.

H2: The more product risk a consumer perceives prior to the purchase of a camera, the more will he or she consult detailed product information.

4.2.2 Exogenous Model Constructs

Referring to earlier information search studies, the concepts of cost and benefit of search, product knowledge, product experience and purchase involvement were included in this model of online search.

A recognized construct in structural equation models of information search [Srinivasan and Ratchford, 1991; Punj and Staelin, 1983] (and theoretical reflections thereon) [Moorthy et al., 1997] are the costs and benefits of search. Costs of search in these studies represent the accumulation of physical and cognitive effort as well as monetary expenditures necessary to find the right product. Benefits of search have been described as satisfaction with the product chosen or cost savings realized through the search activity [Punj and Staelin, 1983]. Benefits have also been recognized in relation to the degree of uncertainty present in the choice of environment, risk aversion and the importance a buyer gives to the product category sought [Moorthy et al., 1997].

In an online context, *cost and benefits of search* will probably continue to trigger search effort. Yet, especially the cost side may be of different nature online than offline. As was mentioned above, academics have pointed to a reduction of search costs in online environments [Alba et al., 1997]. In fact, many traditional search cost variables (such as the physical effort to travel to stores, the implied transportation cost or the cost of cognitive effort to handle the complexity of product comparison) may be comparatively less important in online environments than offline. At the same time, two traditional information search cost factors, namely information processing time and ease of access to information, were shown to continue to play a role for online environments, their design and consumer product choice [Lynch and Ariely, 2000; Hoque and Lohse, 1999]. Both of these cost factors are linked to the time investment a user is willing to make as part of the online search process.[24] Thus, even though the time required for an online search is already minimal in comparison with the offline world, it still appears to play a role in the way consumers search for information. As a result, time cost has been included in our model of online information search. While the named studies investigated the information search cost construct only for user driven information search, referring mostly to product listings, the model hypothesizes that time cost may be equally important in an interaction process with an agent. After all, consumers may weigh the number of specifications they make and potentially skip interactive search categories (in our case any of the 7-question cycles) in order to minimize time investment. Two hypotheses have been derived:

[24] In the Hoque and Lohse study [1999] information processing effort was, in fact, measured on the basis of time investment per online task (such as moving the mouse) while in the study conducted by Lynch and Ariely [2000] this time investment was implied through the experimental set-up.

H3: The more time cost a consumer perceives while searching for product information, the less will he or she interact with an electronic sales agent.

H4: The more time cost a consumer perceives while searching for product information, the less they will consult detailed product information.

Costs of search have traditionally been outweighed by their benefits. For online environments this argument will probably continue to hold true. As in offline environments the benefits of search reside in the identification of an appropriate product. If consumers feel that interacting with an agent helps them to identify the right product they will probably be ready to invest into a relatively extensive dialogue (at least in a high-involvement context). If agent interaction is, however, thus beneficial, they will probably invest less effort into manual searching. To stress the relevance of perceived benefits from agent interaction for online information search, it was hypothesised that:

H5: The more benefits a consumer perceives from interacting with an agent, the more they will interact with it.

H6: The more benefits a consumer perceives from interacting with an agent, the less will he or she consult detailed product information.

Another construct that has continuously been shown to influence offline information search is *product knowledge* [Srinivasan and Ratchford, 1991, Beatty and Smith, 1987, Punj and Staelin, 1983]. Yet, what consumers actually know about a product category (objective knowledge) and what they think they know (subjective knowledge) is often differing and may have diverging effects on search [Brucks, 1985]. As a result, the empirical findings on how knowledge influences search have been contradictory. For the purpose of the current study there has been a focus on the knowledge consumers claim to have on a product category, because in the end it is this subjective feeling that will drive search effort. Subjective product knowledge was expected to limit searches by allowing responses to become routine or by allowing relevant information to be easier separated from the irrelevant, especially when interacting with an agent system. On the other hand, it was thought that higher levels of subjective product class knowledge would lead subjects to increase manual search, since it allows one to delve deeper into information material. In addition, it was argued that those consumers who have more knowledge on a product also perceive less purchase risk [Sundaram and Taylor, 1998; Srinivasan and Ratchford, 1991]. It was therefore hypothesized that:

H7: The more knowledge a person states to have about a product category, the less will he or she interact with an electronic advisor agent.

H8: The more knowledge a person states to have about a product category, the more will he or she consult detailed product information.

H9: The more knowledge a person states to have about a product category, the less risk will he or she perceive when confronted with a buying situation in the respective category in an online context.

A concept that has gained considerable recognition in the study of information search and that has already been introduced in section 2.3.1. is the *level of involvement* a consumer has with the purchase situation (see e.g. [Beatty and Smith, 1987, Punj and Steward, 1983]). Involvement is seen as a motivational factor in consumer choice behavior and is attributed mainly to three causes [Deimel, 1989]: personal predisposition (i.e. subjective needs or goals), situational factors (e.g. time pressure) or stimulus-dependant factors (e.g. influence of product or communication). While situational involvement has been integrated in the model as a separate construct, stimulus-dependant involvement has been seized indirectly through the construct of product knowledge and perceived risk. Involvement was expected to play on both, agent interaction and manual search. A number of authors have argued that purchase involvement is also closely related to the consequences element of perceived risk [Beatty and Smith, 1987]. It was therefore hypothesised that:

H10: The more involvement a consumer has with a purchase situation, the more will he or she interact with an electronic sales agent.

H11: The more involvement a consumer has with a purchase situation, the more will he or she consult detailed product information.

H12: The more involvement a consumer has with a purchase situation, the more risk will he or she perceive when confronted with a buying situation in an online context.

A number of studies have addressed the subject of consumer interactivity, and information exchange with first generation computer mediated environments. For example, based on the theory of exchange developed in marketing literature, Swaminathan et al. [1999] tested the impact of vendor characteristics, transaction security, privacy concerns and customer characteristics on the likelihood of electronic exchange. Other studies observed the importance of secure financial transactions for consumers' perceived risk in online transactions [Parachiv and Zaharia, 2000]. By far the greatest research attention has, however, been attributed to the impact of privacy concerns on information exchange [Culnan and Milberg, 1999; Swaminathan et al., 1999; Hoffman and Novak, 1999] and to the existence of flow in online navigation [Hoffman und Novak 1996, 2000]. These two constructs, privacy and flow, have therefore been integrated in our online search model.

Privacy concerns of online users are a hotly debated issue. As mentioned above, studies confirm that consumers have great concerns about breaches of privacy [Pew Internet & American Life Project, 2000; Ackerman et al., 1999; Hoffman et al., 1999; Westin, 1996]. Ackermann et al. [1999], for example, found three distinct groups of online users with different levels of privacy concern: marginally concerned users, a pragmatic majority and privacy fundamentalists. Yet, despite these concerns many Internet users do not possess even rudimentary levels of online surveillance knowledge, and they do not use the available tools to protect themselves [Pew Internet & American Life Project, 2000]. As a result, the relationship between privacy concern and subsequent behavior is unclear. Would users restrict online exchange in order to protect themselves? Swaminathan et al. [1999] suggested in an empirical study among 428 users that this might be so. However, as is the case with most privacy surveys, they only based their model findings on questionnaire data and lag observations of consistent action. How might people react to a friendly anthropomorphic agent that gives good product advice in exchange for private information?

Privacy can be sacrificed by both interacting with an agent, or by simply navigating online sites. All activities are usually logged by several servers that host the content displayed on users' screens. However, as was outlined above, when consumers interact with advisor agents on website (which ask for key-words or retrieve personal data through dialogue-based systems) they reveal a considerable amount of direct personal information. Consumers were therefore expected to be particularly cautious when using the interactive applications leading to the hypothesis:

H13: The more privacy concern a consumer expresses over the revelation of personal data, the less will he or she interact with an electronic sales agent.

Another phenomenon apparently occurring when navigating in online environments is 'flow'. This flow status is a psychological state that has been investigated in the context of intrinsic motivation since the 1960's [Csikszentmihaly, 1995]. Hoffman and Novak observed its relevance for online environments [1996, 2000] and defined it here [2000, p.23] as a *"state occurring during network navigation which is: (1) characterized by a seamless sequence of responses facilitated by machine interaction, (2) intrinsically enjoyable, (3) accompanied by a loss of self-consciousness, and (4) self-reinforcing."* Thus, when consumers search for information online, it is possible that they lose perception of time and keep on navigating longer and in more directions than they initially planned to. Seen the creation of flow in online environments, the aim was to control this phenomenon with the following hypotheses:

H14: The more flow a consumer perceives, the more will he or she interact with an electronic sales agent.

H15: The more flow a consumer perceives, the more will he or she consult detailed product information.

Finally, it is intuitive to suggest that online consumers who used physical retail channels to get an overview of the product category and are thus more advanced in the buying process than their peers, would engage in less information search online than those who entered the online search process unprepared. The reason for this is that in interacting with an agent, informed customers might already know what selection criteria are the most important for them and are able not only to reduce the number of search criteria to a reasonably small size, but can also make up their mind more quickly regarding the specifications they prefer. As they know what they want, they may also be able to view product alternatives quicker and understand detailed product information more easily. Even though the stage in the buying process and product knowledge are related concepts, they have been distinguished for modelling purposes. Consumers could have felt knowledgeable about a product category without having gone to a store in advance of the online shopping trip. At the same time, subjects may have gone to a store before shopping online, but still felt little knowledgeable about the product category. Given this, it was hypothesized that:

H16: The further a consumer is advanced in the buying process, the less will he or she interact with an electronic sales agent.

H17: The further a consumer is advanced in the buying process, the less will he or she consult detailed product information.

H18: The further a consumer is advanced in the buying process, the less risk will he or she perceive when confronted with a buying situation in an online context.

4.3 Measures

4.3.1 Measurement of Endogenous Model Constructs

4.3.1.1 Measurement of the Information Search Construct

In the literature on offline information search, search activity has typically been operationalized by the time employed, the number of stores visited, the number of product alternatives inspected, the number of friends consulted etc. [Beatty and

Smith, 1987, Punj and Staelin, 1983]. For the purpose of the current study, measuring information search levels had to be adjusted to the electronic medium. While the relative amount of time spent searching was kept as one factor representing the search effort, the number of page requests was added as a second measure. Time was recorded for interaction with the electronic agent (phase 2) and for the two product inspection periods (phases 1 & 3). The time for interaction with the agent has been represented through the total time spent on answering agent questions and going back to the 7 category survey-page. The number of page requests in the context of agent interactivity stand for the intensity of exchange a user sought with the electronic agent. As was described above, the agent asked 56 purchase related questions, each of them representing a separate page. Users could return to this interactive functionality at any time during the shopping process and modify answers initially given. This activity of modifying specifications added to the number of pages requests in the interaction cycle as well as the time spent on the functionality. Finally, calls for the Top-10 ranking originating from the agent dialogue or the 7 category survey-page have been added to the number of page requests representing the breadth of agent interaction.

The number of individual product alternatives viewed added to the manual search construct. Each camera model on offer in the online shop was described on a separate html-page that could either be viewed in phase 1 or in phase 3. In addition to this detailed description, users had the possibility (in phase 3) to enlarge the photograph of each object in a separate page. The number of photo enlargements have been added as additional page requests to the construct of manual search. Finally, product descriptions were always requested from a page that listed the models available; either the Top-10 product ranking or the initial product orientation list (in phase 1). Together, product model lists, factual descriptions and photo enlargements made up the number of page requests for the dependant manual search construct. For all these pages time has been recorded and taken as a second measure. Both measures, time and page requests, are extremely precise measures of search when compared to the effort recall measures traditionally used in offline studies on information search.

Both time and page requests were recorded until a participant ended the search process which could be done either by pressing the ‘buy-button’ or the ‘exit-button’.

Time and page requests were also the only model constructs that were automatically recorded by the system. All the other measures were derived from participants' answers to pre- and post-shopping questionnaires. Appendix B1 gives again an overview of the different site pages and table C2 in Appendix C of the measures used.

It could be argued that the choice of time as a metric for the search undertaken is questionable since subjects have been asked to stay for a specified minimum of time at the lab. The time-cost factor that is usually present in shopping activities was therefore slightly manipulated. In fact, briefing the participants in this way may have led to a reduction in the variance of the time variable. However, the variance finally observed can be attributed more effectively to the constructs tested and is less subject to personal motivations in time management that would otherwise have gone uncontrolled. In addition, most of the subjects spent more time in the laboratory than they had to. It can therefore be argued that time is still a good measure; particularly as is was only important to observe the *relative* differences in behavior present in treatments with the same time conditions.

4.3.1.2 Measurement of Perceived Product Risk

Previous work was referred to in order to measure product category risk . As was outlined above, perceived risk has been characterized as a multidimensional construct with people differentiating between several negative consequences of a purchase including functional, financial, sociological and psychological risk [Kaplan et al., 1974]. For the current model, risk dimensions have been combined into one overall index (that has been proposed and tested by academics in earlier studies [Peter and Tarpey, 1975, p.30]). As a result, risk has been captured in the following way:

$$OPR_j = \sum_{i=1}^{n} (PL_{ij} \cdot IL_{ij})$$

with ORPj = overall perceived risk for brand j

PL ij = probability of loss i from the purchase of brand j

IL ij = importance of loss i from purchase of brand j

n = risk facets (here n = 4)

OPR contains two components: *"…a chance aspect where the focus is on probability [of losing] and a 'danger' aspect where the emphasis is on severity of negative consequences of purchase"* [Kogan and Wallach, 1964 cited in Peter and Tarpey, 1975, p.30]. Cunningham [1967] originally suggested a multiplicative relationship.

In the pre-shopping questionnaire, risk perception was measured by employing a 15-point scale for both dimensions, probability and importance of loss (see pre-shopping questionnaire in Appendix A5a). In order to calibrate the way in which different people respond to scales, each individual had to rate not only camera purchases, but also potential dangers and probabilities of loss associated with 'extreme products' in terms of risk, namely toothpaste and used automobiles.

4.3.2 Measurement of Exogenous Model Constructs

In order to measure time cost, earlier studies were considered which have introduced the idea of measuring time cost as opportunity cost. For example, Srinivasan and Ratchford [1991] measured time cost by asking people for their general time constraints and implied that this perception would be a measure for the opportunity cost perceived while searching for product information. In the present study, time cost was therefore grasped similarly by asking participants after shopping whether they had had the feeling during search that they would have rather done something else instead of sitting in a lab.

The problem in specifying the benefit construct is that, strictly speaking, benefits are not an antecedent, but a result of search. More precisely, perceived benefits of search are the anticipated result of each additional search step performed [Moorthy, 1997; Weitzman, 1979]. Studies that measure the benefits of search should therefore try to capture either expected or ongoing benefits of search. This, however, has turned out to be a challenge. Either studies referred to the post satisfaction with the product bought [Srinivasan and Ratchford, 1991] or employed very general measures testing for consumers' backward belief in the merits of the search activity [Srinivasan and Ratchford, 1991]. Doing so, self justification may have impacted responses. On the other hand, measuring expected benefits of search prior to the actual search taking place carries the risk to prime subjects' behavior. The measurement problem was attempted to be circumvented by taking the perceived quality of agent recommendations as an indicator for perceived search benefits. Doing so, neither self-justification effects were present in our measure nor have subjects been primed. Instead, it has been possible to capture participants' ongoing impression of the quality of exchange, (closely linked to the identification of the right object.

For the measurement of product knowledge and involvement, measures have been used in the current study that have been proposed and tested in earlier empirical works [Srinivasan and Ratchford, 1991, Moore and Lehmann, 1980]. Table C2 in Appendix C gives a detailed overview of questions employed.

For the measurement of the two variables privacy and flow identified to be relevant for online environments parts of recent studies on these subjects have been employed. To measure privacy concerns some of the scales developed by Ackerman et al. [1999] were used. Participants were asked ten questions reflecting to what degree they would be ready to reveal certain types of information about themselves on a web site , including identification information (e.g. address or name) and profiling information (e.g. hobbies or income). The arithmetic mean of answers given to these 10 questions provided an index for participants' privacy concerns.

Flow is a construct that is relatively complex to measure. In psychological experiments conducted by Csikszentmihalyi et al. [1995], the so-called Experience Sampling Method (ESM) has been employed which involves permanent and unexpected measurement of the current state of consciousness during an activity. Thus, upon a notification signal of a transmitter that subjects have to carry with them, they are required to respond to a short questionnaire (so called *random activity information sheet*) testing their current state of being. As a constant measurement of flow was not practicable in the shopping experiment, an additive index has been developed that is based on a number of questions capturing the flow experience as defined by Csikszentmihalyi et al. [1995] and Hoffman and Novak [2000]. The questions used to measure flow were derived from the random activity information sheets used in ESM experiments and attempted to capture what Hoffman and Novak [2000, p.24] characterized as the cognitive state of flow on the Web which would be *"determined by (1) high levels of skill and control, (2) high levels of challenge and arousal, (3) focused attention and (4) is enhanced by interactivity and telepresence"*

Finally, the fact that some participants had gone to a physical retail outlet was taken into account in advance of the experiment. There, some had already chosen products of interest for themselves that they now wished to buy for a 60% discount in our online store. Even though the online store made it difficult for them to rapidly identify their consideration set, because there were not brand names displayed, these subjects might still have behaved differently to those who were not informed. Subjects were therefore asked in advance of the buying session whether they had informed themselves of the product they wanted to purchase before coming to the lab and also to what degree they had already decided on products (consideration set). The two answers given were then combined to one index entitled *Stage in the Buying Process.*

Table C2 in Appendix C gives a detailed overview of all measures for the different constructs integrated in the equation model of information search. A major limitation of construct measurement is that constructs usually did not have more than 1 or 2 indicators. More precisely, the models captures 4 constructs (privacy concern, flow, perceived risk, stage in the buying process) with the help of an index, 4 other constructs (purchase involvement, product knowledge and the online search variables) with the help of 2 indicators and finally, costs and benefits of search with only one indicator. The reason why model constructs had to be concentrated in this way is that for equation modelling the recommended ratio of sample size to number of free parameters is about 5:1 [Bentler and Chou, 1987]. As was mentioned above, the study was restricted in terms of sample size, which implied that the number of free model parameters had to be minimized. Using reliable indices as construct representatives was a reasonable strategy to do so.

4.4 Results

4.4.1 Data

Before model estimation, the data (see table 2) was screened for outliers[25] which led to an exclusion of 6 from a total of 151[26] observations. In addition, 29 subjects had missing data, which could have been imputed [Little and Rubin, 1987]. However, imputing missing values by using a Maximum-Likelihood approach implies a multivariate normality assumption. As this assumption does not hold true for our data basis[27], model estimation had to be based on 116 cases.

4.4.2 Model Estimation and Fit

A structural equation modelling approach was used to simultaneously test model constructs and their relations. This approach was chosen, because it allowed for the test of complex relationships between constructs and also, to some extend, operationalized theoretical constructs by multiple items. The model was estimated by the software program Mplus [Muthén and Muthén 1998] which uses Maximum-Likelihood Method (MLM) as a standard modelling approach. Yet, since data

[25] The respect of time measures for information search in the model required an outlier analysis in order to take account of two phenomena: 1) some users had proceeded to the first page of 'orientation' without the experimenters' consent and before having answered the prior-to-shopping questionnaire. Even though orientation was interrupted, time was recorded for these participants on the respective level. 2) some users had to leave for the restroom during the shopping session.

[26] As summarized in table 1, the original data set included 152 subjects. However, 1 subject did not answer the correct questionnaire version prior to shopping and therefore had to be excluded from analysis.

[27] Using PRELIS 2.30 [Jöreskog and Sörbom, 1996] the assumption was tested that the variables are normally distributed. The multivariate tests (see for example [Bollen, 1989]) after listwise deletion of 29 cases with missing data show that the remaining data is, however, significantly skewed ($z = 5.42$, $p = .000$) while multivariate kurtosis represents a borderline case ($z = 2.45$, $p = .014$). An omnibus test on multivariate skewness and kurtosis ($\chi^2 = 35.37$, $p = .000$) further indicates that the data is not normally distributed, although deviation from the norm seems to be rather modest and in the first place concerns indicators for information search behavior.

deviated from the normality assumption that underlies a Maximum-Likelihood (ML) estimation it was necessary to use the more robust MLM estimation option available in Mplus. This MLM estimation approach respects the condition of a relatively small number of observations as well as deviations from normality distribution. It usually has an effect on estimated standard errors for parameter estimates as well as the Chi-square test statistic.

In an initial model estimation thus conducted with MLM, adequate fit indices were obtained. However, four of the latent variable indicators had negative measurement error variances. These so-called "Heywood cases" are a problem often encountered in structural equation modelling under the conditions of a small sample size and only two indicators per latent variable [Boomsma 1982; Anderson and Gerbing 1984]. As neither sample size nor the number of indicators could, however, be changed, the problem of improperty was solved by employing a strategy pursued by earlier studies on information search where negative error variances have been set to zero [Punj and Staelin, 1983]. Recalculating the model with the time variable for manual search being set to zero resolved the negative error variance problem for the entire data set. In addition, modification indices that can be generated by ML-estimation suggested a considerable increase in model fit by specifying a covariance between the measurement errors of two search indicators, namely the number of page requests during the interaction with the agent as well as those requested for manual search. From a theoretical point of view this correlation makes, in fact, sense in that the two constructs of agent interaction both represent facets of information search for which some unobserved but common variable carries explanatory value.

Standard fit measures in structural equation modelling obtained for the final model are highly satisfactory (see table 3) [Homburg and Baumgartner, 1995]. The RMSEA is considerably below the cut-off value of .05 [Browne and Cudeck 1993; Hu and Bentler 1999] and both CFI and TLI are above the threshold value of .95 [Hu and Bentler 1998]. [28] Table C2 in Appendix C contains the system output corresponding to the results reported.

[28] To further support model validity the MLM-fit was challenged by additionally re-calculating the model with the more standard Maximum Likelihood (ML)-estimation. Here a *moderate* fit was confirmed with an RMSEA =

Tabelle 3Fit Measueres for Model of Online Information Search:

Overall Model Fit (MLM)
$\chi^2_{(44)} = 51.52$ RMSEA = .038 CFI = .974 TLI = .952 $\hat{R}^2_{RISK} = .065$ $\hat{R}^2_{INT\_ACT} = .208$ $\hat{R}^2_{INSPECT} = .194$

The rather small sample size prevented a highly sophisticated operationalization of the theoretical constructs by multiple indicators. Nevertheless, based on parameter estimates for the model, the reliability and validity of our two-indicator measurement models has been assessed (see table 4). For this purpose indicator reliability was used [Bagozzi, 1982], factor reliability (squared correlation between a construct and an unweighed composite of its indicators; see [Bagozzi and Baumgartner, 1994]) and the average variance extracted [Fornell and Larcker, 1981]. Both, factor reliability and average variance extracted can be regarded as measures for convergent validity. Since all these values were above the required threshold values [Bagozzi and Yi, 1988] and as factor loadings were all significant, the construct measurements can be regarded as reliable and valid (see table 4).

.077, CFI = .919 and TLI = .851. However, since for small samples these fit criteria tend to over-reject true population models [Bentler and Yuan, 1999; Hu and Bentler 1998] these values should be regarded with caution.

Tabelle 4 Reliability and Validity of Measurement Models:

Factor	Indicator	Indicator Reliability	Factor Reliability	Average variance extracted
Involvement	1	.908	.841	.747
	2	.431		
Product class knowledge	1	.978	.811	.688
	2	.438		
Interaction with agent	1	.848	.761	.615
	2	.455		
*Product inspection	1	1.000*	.864	.761
	2	.626		
Required level		≥ .4	≥ .6	≥ .5
*error variance fixed to zero				

4.4.3 Model Relationships

Fit measures of the model indicate that the overall relationships hypothecated to exist for online information search sufficiently reflect reality. Interesting for the better comprehension of online information search is, however, to what extend the hypotheses made hold true and at what level of significance they can be supported. Figure 6 gives an overview of the findings (for detailed output data see Appendix C, table C3).

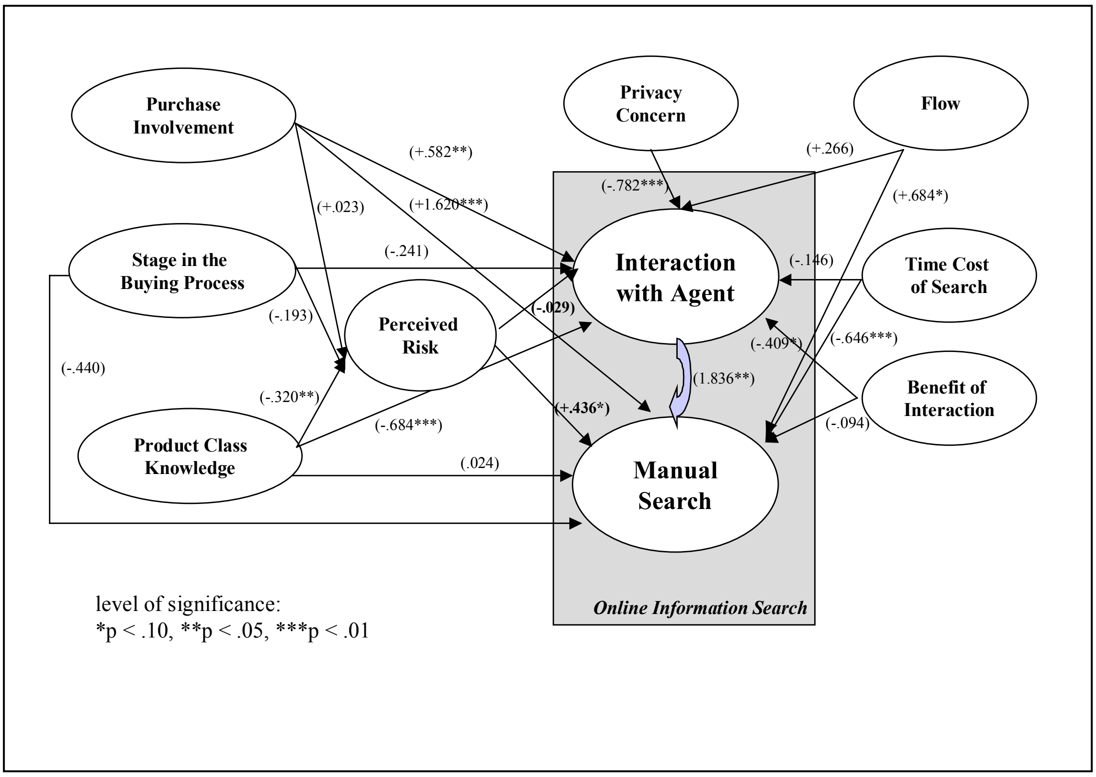


Abbildung 6: Antecedent Variables and Directionality of Relationships for a Model of Online Information Search

In hypotheses 1 and 2 it was postulated that the more purchase risk a consumer perceives the more will he or she search for information. In fact, hypothesis 1 that users use an electronic agent more intensively when they perceive higher levels of risk was not confirmed by the data. In contrast, it was observed that participants tended to rely less heavily on the interactive functionality the more risk they perceived, even though this relation is not significant. At the same time, they consulted significantly more detailed product information the more risk they perceived, confirming hypothesis 2. This finding suggests that consumers may engage more in manually controlled forms of search the more product risk they perceive. At the same time, they do not necessarily like to rely on an interactive functionality like agent Luci. In the section 4.5. below this phenomenon is commented on in more detail.

All exogenous constructs that were hypothesized to influence the perception of risk, namely product knowledge (H9), purchase involvement (H12) and the stage in the buying process (H18) proved to be in the right direction. However, none of them were statistically significant, except for product knowledge.

As far as the time cost of search is concerned, hypothesis 4 was supported. The data revealed that the more participants had wished to do something else while shopping online, the less they manually sought for information. The same was true for agent interaction (hypothesis 3), however not to a significant level. The results might indicate that agent functionality is relatively less impacted by consumers' time constraints than are user-driven search forms. This, however, would have to be proven by more research.

In contrast to hypothesis 5, the more benefits a user derived from their interaction, the less he or she was willing to invest in the interaction process. In fact, since that benefits of search were measured in the form of perceived accuracy of agent recommendation, it is intuitive to argue that the better the initial recommendation made by the agent, the less participants had an incentive to return to the interactive functionality to enhance or modify search parameters. However, even if this explanation is straight forward, the finding is still interesting because it raises awareness that one of the most basic assumptions made in information economics, which is that the more benefits one retrieves from information search, the more one searches for information, might be significantly impacted by agent technology (at least if benefits are measured in terms of identifying the right model). This impact resides in the possibility that the perceived utility of search renders decreasing marginal returns of search much quicker than this was the case for offline markets. The result is an inverse relationship between perceived search benefits and the activity of search. More research is certainly needed to investigate this finding and test its impact on the cost-benefit construct in information search theory. Hypothesis 6 that the more benefits a consumer perceives from interacting with an agent, the less will he or she consult detailed product information was supported by the data, however not at a significant level.

The traditional concept of product knowledge proved to be a reliable indicator for the prediction of interaction with the agent. Hypothesis 7 that the more knowledge a person states to have about a product category, the less will he or she interact with an electronic sales agent was shown to be significant at the highest level. Also, the positive effect of product knowledge on manual search was in line with the initial hypothesis (H8), though not at a significant level. Thus, people who think that they know a lot about a product relied less on an advisor agent, spending less time and effort on interaction with it. At the same time, they had a slight tendency to invest themselves more in manual search.

Another traditional search factor which proved highly significant for both parameters of search, agent interaction and detailed product inspection, was product involvement (H10 and H11). The more involvement a participant had with the purchase situation, the more he or she used both information sources available from the online store.

In summary, most of the traditional information search factors identified for offline markets were supported by the online model, with more than half of them at a significant level. Only two relationships did not hold true, namely the impact of perceived risk, and search benefits on the interaction process with the agent.

Hypothesis 13 that privacy concerns would be negatively related to consumer willingness to interact with the agent system was confirmed by model results. In fact, the data does not only support hypothesis 13, but also suggests that privacy concerns may have the strongest impact on agent interaction amongst all variables tested. This finding means that marketers who employ highly interactive technologies on their web sites should, in their own interests, pay attention to the privacy conditions they offer to their customers. However, it should also be noted here that in average more than 85% of the agent's questions were answered by the participants. This is surprising, because answering agent questions is much more informative about a user than his navigating a site. Users' privacy concerns seem to have expressed themselves more in a restriction of navigation (measurable in time and page requests) than in a reduction on information disclosed. Seeing the contradiction of these findings and also the relevance of privacy for the Net community, privacy preferences and behavior are investigated in more detail in chapter 6 of this thesis.

The flow construct introduced by Hoffman and Novak [1996, 2000] for Web navigation proved significant to the model. The data confirmed that participants who perceived more flow searched significantly more manually (hypothesis 15). This positive effect was, however, not significant in as far as the shopping agent was concerned (hypothesis 14).

Finally, the data supported at a non-significant level that the more participants were advanced in the buying process, the less would they interact with the advisor agent (hypothesis 16) or manually search for information (hypothesis 17). As there were no brand names displayed in the store, the strength of this finding must, however, be regarded with caution. In case of brand display the negative effect on information search could have been stronger, with participants going directly for their consideration set.

4.5 Discussion: Strategies of Information Search With or Without Agents

An interesting finding of the structural equation model was that both higher levels of perceived product risk and product knowledge did not seem to lead to higher levels of interaction with the agent.

The more product knowledge a participant stated to have about cameras, the less he interacted with agent Luci. At the same time a positive relationship was observed regarding manual search. This goes in line with Urban et al.'s findings [1999], who found similar evidence that subjects with higher levels of product knowledge reported to prefer less reliance on an advisor-agent. Does this mean that consumers generally appreciate agents less the more they know about a product category? In order to investigate this question, the data was analysed in more detail.

The results of the structural equation model as well as those obtained by Urban et al. [1999] were impacted by the type of agent employed in the experiments and its specific perception by users. Both systems offered an in-depth dialogue system and wished to support a cross-section of product knowledge levels. As a result, some highly knowledgeable customers may not have found the level of expert-exchange they wished for. In short, reduced levels of interaction (actual or reported) could also be attributable to low satisfaction levels with the very agent system employed in the experiment.

In order to investigate this argument, the relationship between subjective product knowledge and the level of satisfaction with the advisor agent was analysed which was measured after the shopping session. First, the two questions that had been employed to measure subjective product knowledge (K_A, K_B) were correlated with satisfaction levels (S_L).[29] A negative correlation would suggest that more knowledgeable customers did not appreciate then interaction with agent Luci which indicates that the specific agent employed in the current experiment was not ideal for more knowledgeable customers. In case of a positive correlation, support would be given to the argument that, even if more knowledgeable users appreciated the agent system, they were generally less relying on it for their product choice.

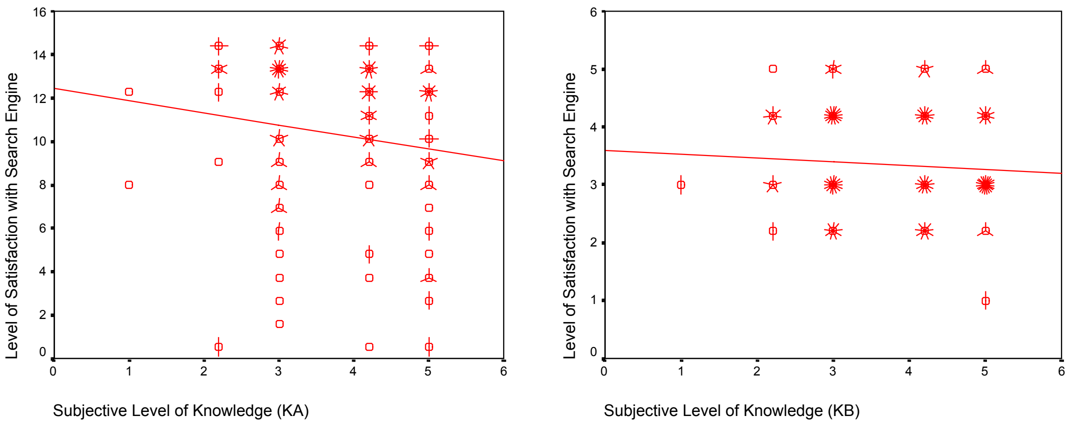
Table 5 indicates a negative correlation between product knowledge and satisfaction with agent Luci. The more knowledge a participant stated to have in comparison to the average citizen (K_A), the less did he appreciate the agent which is expressed in a significant negative correlation coefficient CORR (S_L, K_A) = -.167*.

The correlations suggest that lower levels of interaction could be attributable to the failure of the very agent system employed in the experiment to serve the needs of highly knowledgeable customers. As a result, it cannot be argued that, in general, higher levels of product knowledge lead to lower levels of interaction with agents. More research on this aspect would certainly be of interest.

[29] Satisfaction with the agent (S_L) was measured by asking users after the shopping session: "What level of comfort did you perceive in interacting with the search engine?" Participants answered on a 14-point scale from 1= no comfort at all to 14 = very high level of comfort

Tabelle 5 Relationship between Subjective Product Knowledge and Satisfaction with the Search Engine :

A:Subjective Level of Product Knowledge (KA):	**B:Subjective Level of Product Knowledge (KB):**
In comparison to the average citizen I already know quite a lot about hifi-equipment (e.g. stereos, cameras, TVs..)	I regularly advise peers in the choice of their electronics.
5 = very true 4 = quite true 3 = depends 2 = not really 1 = not at all	5 = very true 4 = quite true 3 = depends 2 = not really 1 = not at all
CORR (S_L, K_A) = -.167* (*p = .044)	CORR (S_L, K_B) = -.016 (p = .848)



Interpreting model results on perceived risk, similar observations were made as to the use of the two search forms offered in the online store: The more risk participants perceived prior to a purchase, the less they relied upon agent interaction (non significant relation) and the more they searched manually for information on each object. As argued above, this finding suggests that consumers may rely more on manually controlled forms of information search the more risk they seek to reduce.

Again, in order to support this type of generalized argument, it was important to exclude the possibility that it was the quality of exchange offered by agent Luci in particular that led to the observation of the relationship. Investigating the relationship between perceived purchase risk prior to shopping (R_P) and general satisfaction with the shopping agent (S_L), however, suggests that satisfaction with the search engine and risk perception are two relatively independent constructs in our data; the correlation coefficient CORR (S_L, R_P) = - .069 being small and not significant. Also, when looking into the relationship between risk and satisfaction with the agent recommendation quality (S_R) this independence is maintained displaying a non-significant correlation coefficient of CORR (S_L, R_P) = -.060.[30] Thus, the observation that participants used the agent in a relatively restricted manner the more risk they perceived cannot be attributed to low levels of satisfaction with the system or its recommendations (for SPSS output file see Appendix D, table D2). In addition, and as was outlined above, the agent dialogue was explicitly designed to address all major dimensions of risk with 64% of questions addressing functional, 9% financial, 9% sociological and 18% psychological risk. The experimental data therefore suggest that the more purchase risk a participant perceived the less he chose to rely on the automatic recommendation technology, seeking instead the control over the choice process. Of course, more research would be needed to confirm this finding which may be an indicator for the degree of acceptance (or reluctance) agent technologies will face when being deployed in high-involvement and high-risk electronic commerce environments.

4.6 Conclusion

The structural equation model proposed for drivers and impediments of online information search displayed a very good level of fit and supported the majority of hypotheses made. As a result, it was possible to show that determinants of information search identified in offline studies, including product knowledge,

[30] Recommendation quality (S_R) was measured by asking participants after the shopping session on a 5-point scale: "How well did you perceive product recommendations to fit your needs?"

purchase involvement and time cost, seem to hold true for the online world. Furthermore, (prove could be made of the influence of new variables such as privacy concerns and the achievement of a flow status for information search behavior in electronic environments.

As far as agent based versus manually controlled forms of search are concerned, it is interesting to see that consumers who perceived higher levels of risk prior to the purchase relied less strongly on agent advice than their peers and preferred to control the search process manually through product inspection. As far as product knowledge is concerned, the data suggest a similar tendency for more knowledgeable customers to rely less on agent advice. However, more research would be needed to confirm this finding. In addition to these potential impediments for agent use, risk and product knowledge, it was interesting to see that perceived time cost led to a smaller influence on agent interaction than on manually controlled forms of search. At the same time, agent interaction seemed to create less flow.

In line with the hypothesis made on privacy, expressed privacy concerns of participants seem to have led to reduced levels of interaction with the agent. However, this is a curious finding, since participants answered in average over 85% of agent questions. Thus, decreased levels of interaction stand in sharp contrast to the actual information disclosed. A more detailed analysis of this behavioral phenomenon is presented in chapter 6.

All in all, valuable insights have been gained on drivers and impediments for online information search with advisor agents and/or manually. An important limitation of the structural equation model presented though is the limited sample size on which it is founded. Also, the fact that there were only a few indicators per construct, often only one index, must be regarded as a drawback. On the other hand, the advantage of the structural equation modelling approach was that one could capture relationships simultaneously and avoid problems of multi-co-linearity often present in regression analysis. The good model fit supports our approach. If there had been serious problems in model set-up, the equation model would not have converged.

Finally, the model was built on only one product category. As other scholars in information search have pointed out, this single-measure, single-product variety limits though the generalizability of the findings [Beatty and Smith, 1987]. As a result, it would be interesting to challenge the findings on a bigger sample size and across several product categories. This was unfortunately not in the scope of the current thesis. However, one finding of particular interest that resulted from the structural equation model was still investigated for another product group: the influence of perceived risk and uncertainty on agent use. Do consumers really seek for more controlled information environments when they shop for higher risk products? Do they tend to rely relatively less on agent advice when they perceive more risk? This question was investigated in more detail, by comparing the concrete search activities participants displayed for winter jackets with those for compact cameras. The next chapter (5) reports on the results of this analysis.

Chapter 5

5 Comparing Online Search Behavior for Different Product Categories

In order to investigate the extend to which perceived purchase risk would influence the use of agents or motivate manual search, shopping behavior was compared for two different product groups for which it was expected to measure different levels of purchase risk: compact cameras and winter jackets. The belief that compact cameras and winter jackets would be perceived differently by experimental participants was based on them being search and experience goods (see below).

In the 1990s a distinction of search, experience, and trust goods developed in information economics [Darby and Karni, 1973; Nelson, 1970] has found an entry into marketing literature of institutional theory [Arnthorsson, 1991; Kaas, 1990, 1995; Weiber and Adler, 1995a, b]. Products with strong search characteristics are distinguished by the fact that they can be fully judged by inspection or equivalent information search prior to purchase. Products with dominant experience characteristics can only be fully judged after purchase and use. They are thus implying a higher purchase risk than do search goods, because the buyer's expectations might be disappointed [Weiber and Adler, 1995b]. Finally, products with trust characteristics are marked by the fact that their quality can neither be judged on before nor after the purchase. Given the proclaimed relationship between product nature and risk, compact cameras and winter jackets were chosen for the current experiment, assuming that they could be considered as relatively good representatives for search and experience goods. Compact cameras usually entail strong search good characteristics as their quality can be well described prior to purchase on the basis of product attributes. In contrast, jackets were considered to be a typical experience good, because one has to wear them and feel the model before assessing the fit.

Based on the observations made in the structural equation model presented above, it was hypothesised that subjects shopping for winter jackets would rely more heavily on manually controlled search than camera shoppers.

5.1 Empirical Survey Design

5.1.1 Data

All treatments summarized in table 1 were originally included in the navigational analysis. However, 11 of the 206 participants had missing data relevant for the analysis and one individual answered the wrong questionnaire. This led to a dataset of 195 observations.

In order to investigate the relatively isolated effect of *product nature* on interaction it was necessary to respect individual factors that could potentially have had a strong influence on interaction, but are independent from product. The dataset of 195 observations (144 cameras, 51 jackets) was therefore investigated and straightened out with a view to three factors that the structural equation model had revealed to influence interaction apart from product: namely privacy concerns, satisfaction with the agent's recommendations and perceived time cost.

An in-depths analysis of privacy concerns revealed that most subjects, even though they stated to be privacy conscious, did not act accordingly [Spiekermann et al., 2001]. Yet, for the purpose of the current research it is important to note that only 3 participants (2 camera shoppers, 1 jacket shopper) expressed considerable privacy concern before entering the online store and also acted consistently with their expressed attitude by refusing most of the interaction with the shopbot (see table 14). These subjects have been excluded from the current analysis. Their behavior cannot be interpreted as a response to the product.

Furthermore, the perception of the search engine's accuracy had a significant influence on interaction. It was measured by asking participants after the shopping session how valuable and accurate they had found the agent's product recommendations. While 78,1% of the participants (group 1) felt that the search engine made either accurate (7,8%), quite accurate (29,2%) or at least accurate (41,1%) recommendations, 21,9% were not fond of the search aid (group 2). Mann-Whitney-U-Test used to investigate the impact of this distinct search engine perception on the total number of page requests yielded significant differences for the two perception groups (z = - 2.716, p = 0,007). As a consequence, 23 camera shoppers and 19 jacket shoppers have been excluded from the analysis presented hereafter (for SPSS output file see Appendix D, table D3).

Finally, following the shopping session participants were asked whether they had rather done something else instead of shopping for a compact camera or winter jacket in our experimental store (measured as time cost in the structural equation model). 6 subjects admitted a relatively strong de-motivation.[31] Mann-Whitney-U-Test for the impact of this de-motivation on the total number of page requests, however, did not yield significant differences in behavior (z = -.341, p = .733), nor did a T-test on the time spent shopping (F = 1.776, p = .886). As a result, the 6 subjects were left in the sample investigated (for SPSS output file see Appendix D, table D4).

Considering the eliminations made from the original data set in accounting for privacy concerns and perception of the search engine, 150 observations remained for further analysis: 119 camera shoppers and 31 jacket shoppers.

5.1.2 Identical Store Design

As was outlined in section 3.3.3, it was vital to design the two store versions for cameras and winter jackets as similarly as possible so that navigational behavior can be attributed to the product nature and not to the store environment. As a result, navigational opportunities and product display were provided in the two store versions including a similar quantity of products on offer, a similar number of attributes used to describe each product and an identical breadth of agent communication.[32] All products had the same price range between 200 – 500 DM ($ 100 – 250).

[31] Motivation was measured on a 9-point scale with 1 = yes, would have very much liked to do something else instead of participating in the shopping experiment and 9 = no, would not at all have liked to do something else.

[32] There were, however, 8 facts listed to describe major attributes of cameras and 6 to describe jackets.

First, it was ensured that satisfaction with agent communication would be comparable for the two store versions. This implied an emphasis on similar levels of performance of the search algorithms used in the two stores. For those subjects whose behavior has been considered in the analysis, there was no significant difference in satisfaction with agent Luci ($z = -.353$, $p = .724$) (for SPSS output file see Appendix D, table D5).

Second, the nature of information exchanged with the agent needed to be perceived similarly. Naturally, however, the nature of information exchanged between the agent and customers had to differ for compact cameras and winter jackets. An effort has therefore been made to align the perception of the communication process by ensuring that question legitimacy and importance would be distributed equally in the two store versions. For this purpose an independent pre-study was conducted where 39 subjects rated each one of the 56 agent questions (112 for both store versions) on a 10-point scale as to their perceived legitimacy and importance in an Internet sales context [Annacker et al., 2001]. Mann-Whitney U-test on the mean perceived question legitimacy of the 56 agent questions confirmed non-significant differences for the two store versions ($z = -.867$, $p = .386$). A T-test on mean perceived question importance of the two agent-question catalogues rendered a similar result ($F = .577$, $p = .450$). Thus, all in all, it seems that the degree of relevance and legitimacy inherent in the sales dialogue was perceived similarly for the two store versions (for SPSS output file see Appendix D, table D6).

Finally, the order in which agent questions would be asked was important, as it has been shown to influence navigation [Hoque and Lohse, 1997]. For this reason, communication was arranged identically in both store versions. It included 7 question cycles for each product with agent questions being arranged in each cycle in an order of decreasing importance.[33]

[33] Importance rating were taken from the independent pre-study (see Appendix C, table C1)

5.2 Choice and Perception of Products

To confirm the assumption that compact cameras and winter jackets would be perceived as search and experience goods respectively and entail different levels of uncertainty, several measures have been proposed by Weiber et al. [1995a]. Weiber et al. [1995a] argue that the degree to which a good can be considered a search, experience or trust good is founded on the uncertainty that a consumer perceives in judging the respective good's quality prior to purchase. Subjects who had come to purchase a winter jacket or compact camera were therefore asked how comfortable they felt (q1) and how probable it would be (q2) to fully judge upon the quality of the product they sought with the help of the Internet. In addition, they were asked how uncertain they felt in general that the product would meet their expectations (q3). The answers, which were given on a 6-point scale, are summarized in table 6. They show that participants felt in average less certain in the judgment of jackets. This perception of uncertainty comes close to statistical significance, however, only for q2. Cross-checking this finding with a larger data-set (where an additional 119 answers to questions q1 to q3 were available) improved the level of significance.[34] It can therefore be argued that the perception of winter jackets as an experience good, with slightly higher levels of purchase uncertainty, is supported by the data, if only weakly. Compact cameras, in contrast, are perceived as a search good with slightly lower levels of purchase uncertainty.

[34] In table 2, 206 observations have been reported on that were collected in 4 treatments. As was mentioned there, two additional treatments were included in the experiment the results of which are not reported in this thesis. As these subjects, however, filled out the same questionnaires as the sample reported on this section their judgement of products can be included in the present analysis.

Tabelle 6 Perception of Experimental Products as Search or Experience Goods:

Questions employed to test perceived product nature as an experience or search good	**Mean Value Winter Jackets**	**Mean Value Compact Cameras**	**Statistics I KS-Test (sample: 150)**	**Statistics II KS-Test (sample: 269)**
Q1: How comfortable are you that, with the help of the Internet, you'll be able to fully judge on all quality characteristics important to you [in the winter jacket]? (1= not at all comfortable (..2,3,4,5) 6= very comfortable)	3,35	3,81	z = .726 p = .668	z = 1.505 p = .022
Q2: Please indicate, how probable it is that in the context of an Internet purchase you'll be able to fully judge on all quality characteristics important to you [in the winter jacket]? (1= not at all probable (…2,3,4,5) 6 = very probable)	2,61	3,36	z = 1.339 p = .055	z = 1.459 p = .028
Q3: Please indicate on a 6-point scale how uncertain you generally feel now, before the purchase of a new winter jacket/compact camera, that [the product] will fully meet your expectations! (1 = very uncertain (…2,3,4,5) 6 = not at all uncertain)	3,35	3,45	z = .414 p = .995	z = .759 p = .613

In addition to the perception of compact cameras and winter jackets as respective search and experience goods with different levels of purchase uncertainty associated to them, the two products were also chosen with a view to different types of risk dimensions expected to be dominant in them. As was described in detail in section 4.3.1., risk was broken down into four dimensions including functional, financial, sociological and psychological risk. Risk was calculated by multiplying the perceived degree of loss and probability of loss for all four dimensions of risk and then summing. On an index level, cameras were perceived to be functionally more risky than jackets. More socio-psychological risk components were associated with the purchase of jackets.

Table 7 summarizes the product risk perceptions actually measured for cameras and jackets. It shows that the two products chosen for the experiment do, in fact, raise different buyer concerns. While compact cameras have a relatively high functional and financial risk, jackets display higher risk levels in the socio and psychological area. However, in contrast to expectations, the overall level of perceived risk (OPR) measured prior to purchase among participants was similar for the two products.[35]

The reason why so similar levels of perceived risk have been observed may have to be attributed to the self-selection process of experimental participants: only those people may have registered for the experiment that are already relatively open to use direct marketing channels such as the Internet and may for this reason be generally less risk averse.

As a result of similar OPR for the two products, observed differences in behavior that are reported on in this chapter cannot be directly attributed to different levels of OPR, but must be more seen in the light of distinct levels of uncertainty to judge on product quality prior to purchase. To a certain extend, of course, risk and uncertainty are related constructs as both integrate a ‘probability-notion’ of a loss to occur. This is mirrored in the significant bivariate correlations between OPR and the levels of uncertainty measured with $CORR_{Q1}$ = -.218 (significant at $p < .01$) and $CORR_{Q2}$ = .-198 (significant at $p < .05$) (for SPSS output file see Appendix D, table D7). However, uncertainty does not respect the magnitude and relevance of loss to a consumer.

[35] These general relationships which are measured here across the whole of 150 participants also hold true when product judgement of only those is considered who were going to purchase or shop for a respective product.

Tabelle 7 Perceived Risk Structure of Experimental Products:

Median of OPR observed across 150 subjects	Perceived Functional risk	Perceived Financial risk	Perceived Psychological risk	Perceived Sociological risk	OPR
Winter jackets	72	72	63	99	318
Compact Cameras	99	96	35	75	316
Statistics: T-test for paired samples (*Wilcoxon Test)	T = 4.380 p = .000	T = 3.738 p = .000	T = -4.349 p = .000	Z = -4.938* p= .000*	T = -.343 p = .732

5.3 Observed Interaction Behavior

The first step to analyze the information search activity for the two product categories was to look at the total time users spent in the online store as well as the time expanded for the three distinct phases of the shopping session (orientation, dialogue and detailed product inspection).[36] In addition, some quantitative measures were considered to describe the way in which camera and jacket shoppers differed in their product inspection behavior. Table 8 gives an overview of the findings.

Table 8 shows that jacket shoppers in total invested around 19% more time (t) into the shopping trip than camera shoppers did; in average an additional 4,7 minutes. Particularly interesting in this context is to what part of the shopping session this time was dedicated. Obviously, participants interested in the experience good jacket attributed considerably more importance to manual product inspection. In average they spent 30% more time here than camera shoppers did (t_i). Analyzing this behavior in more detail, jacket shoppers seem to have invested this time in a significantly larger number of objects viewed (73 versus 40) and more than twice as many photographs enlarged. However, they only required a fraction of time on individual objects when compared to camera shoppers.[37] Thus, jacket shoppers seem

[36] The respect of time required the same outlier analysis described in chapter 4.

[37] It must be recognized here that jacket shoppers had only 6 product attributes displayed while camera shoppers had 8 of them. This means that the different times recorded for cameras and jackets could, strictly speaking, be attributed to this differing number of purchase arguments displayed.

to have quickly 'sifted through' the offer as a whole spending relatively little time per product and judging stronger on visual perceptions than camera shoppers who viewed much less products, but in average invested about twice as much time in the inspection of each individual product. The significantly larger time investment by camera shoppers per product indicates that they must have read most of the fact sheets and marketing texts presented for each product.

Tabelle 8 Comparison of Breadth of Interaction for Cameras and Jackets :

Interaction Indicators (Mean Investment in Product Identification)	Compact Cameras (119)	Winter Jackets (31)	Level of Significance [p]
Time Investment Measures:			
- mean time investment, total (t)	24,5 min (109)	29,2 min (30)	.009*
- mean time for orientation (t_o)	0,7 min (112)	0,4 min (36)	.303**
- mean time for communication (t_d)	12,1 min (115)	13,8 min (31)	.013*
- mean time for detailed product inspection (t_i)	11,5 min (120)	14,9 min (37)	.010*
Manual Product Inspection:			
- n° of products inspected	40	73	.000**
- time per product	0,25 min	0,14 min	.000*
- n° of photo enlargements	7,4	16,9	.000**

(* T-test; **Mann-Whitney U-test)

Besides these time variables, the overall findings summarized in table 8 suggest that jacket shoppers, who felt slightly less certain in the judgment of the product, displayed significantly higher levels of overall activity in the search process. At the same time, they searched in a different manner than camera shoppers did, relying more heavily on the manually controlled forms of search.

However, if the time per product is divided by the number of attributes viewed than there is still a significant difference between the time per product with jacket shoppers spending much less time per product (0,25 min per camera model/8 camera attributes = 0,031 min/attribute and 0,14 min per jacket model/6 jacket attributes = 0,025 min/attribute).

In order to better understand the type of interaction sought by the two shopping groups, two indices were developed. The first index, a *communication quota (Qf),* is a set-based measurement designed to express how much of the shopping process was generally dedicated to communicating with the agent versus obtaining information manually. A second index, a *modification quota (MQR)* was then used to analyze the dialogue that participants sought with the agent in more detail. The communication quota was defined as:

$Q_f = C / I$ with

$C =$ total number of requests for a agent question page (including: those pages that were not answered and return hits to correct initial answers given, question category survey page and requests for Top-10 consideration set)

$I =$ total number of requests for pages giving product information, photo enlargements and required return hits to the top-ten set from both phases (orientation and product inspection)

As can be seen from table 9, camera shoppers have a significantly higher communication quota than jacket shoppers. This means that subjects searching for a camera relied relatively more on the exchange with the agent in their information search process than jacket shoppers did. Even though both groups of participants consulted the shopbot with a similar frequency (e.g. answered a similar amount of questions and made a similar number of modifications to initial specifications), jacket shoppers displayed a significantly higher need for manually controlled product inspection. Figure 6 visualizes these diverging navigational foci by giving a broad overview of the click streams that were observed for camera shoppers (above) and jacket shoppers (below) in the two versions of the online store.

Tabelle 9 Comparison of Depth of Interaction for Cameras and Jackets:

Indicators for Agent Interaction	**Compact Cameras**	**Winter Jackets**	**Level of Sig. (Mann-Whitney-U)**
- mean communication quota [C_f]	1,47	0,76	.000
- share of questions answered	85,98%	87,85%	.699
- median of modifications made [M]	6	7,5	.608
- modification quotas for risk dimensions [MQ_R]			
$MQ_{R=fin}$.	0,55	0,29	.070
$MQ_{R=func}$.	0,30	0,40	.099
$MQ_{R=psy}$	0,08	0,13	.009
$MQ_{R=soc}$	0,23	0,23	.120
- modification quotas for privacy dimensions [MQ_P]			
$MQ_{P=pd}$	0,34	0,37	.844
$MQ_{P=pepr}$	0,47	0,35	.454
$MQ_{P=u}$	0,18	0,45	.028
$MQ_{P=peip}$	0,09	0,12	.019

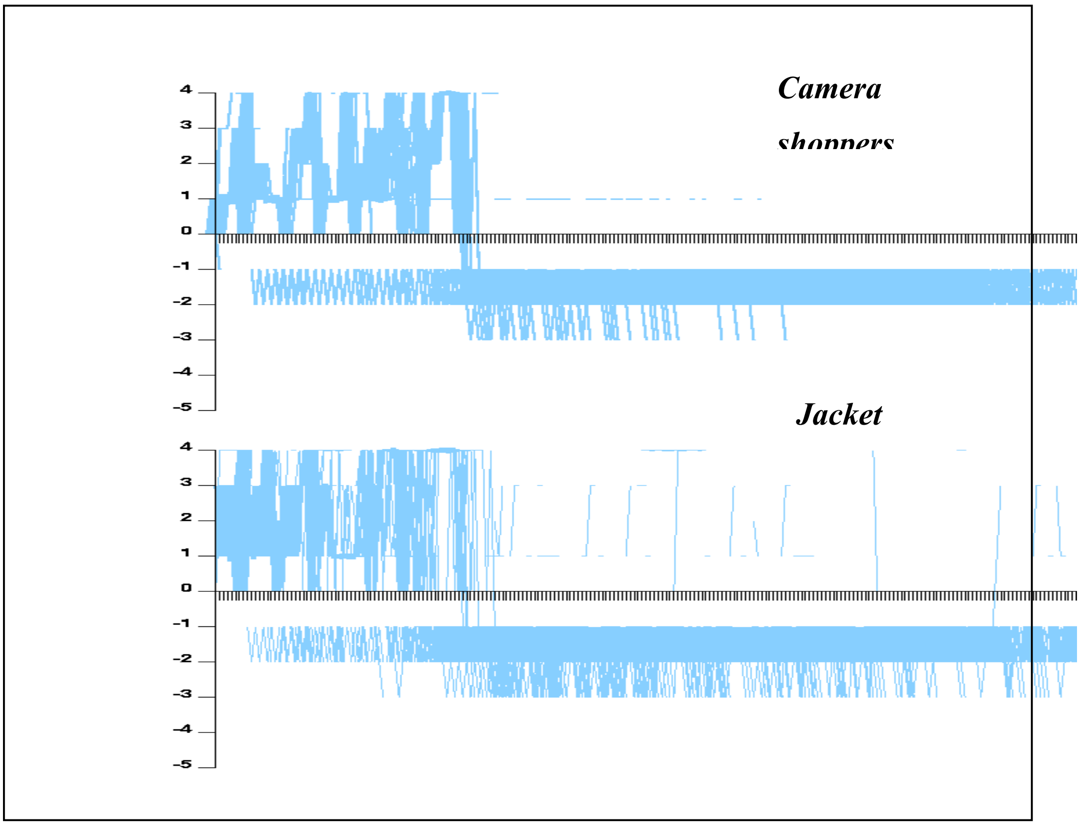


Abbildung 7: Users' Path through the Experimental Online Store[38]

As was outlined above, agent questions were not only product related, but also addressed the user in person and asked for the goals of search (e.g. desired use for the product). Given the wide spectrum of 56 agent questions, one goal of the current analysis was to find out what type of question people would be willing to answer while shopping for one or the other product. A correlation was therefore expected to be seen between the dominant risk dimensions of a product (e.g. social risk for jackets) and users' motivation to answer agent questions best suited to address them. However, as the 150 participants answered in average more than 85% of total agent questions, there would have been a strong ceiling effect present in the analysis of the number and share of questions answered. As a result, an attempt was made to 'grasp' users' qualitative purchase concerns in more detail by investigating the type of

[38] The figure presents 'stratograms' [Berendt, 2001] that trace users' paths through the site. The x-axis contains the steps in the navigation history, while the y-axis represents the type of page requested. Values along the y axis are ordered to reflect the interaction process: 0 is the question category survey page from where users can enter different cycles of agent questions, 1 to 4 is any question page, -1 is the display of product rankings, -2 is the detailed product description and -3 the respective photo enlargement. Navigation presented here starts with the communication phase2.

question modified. For this purpose, a *modification quota* was developed for those subjects that did make adjustments to initial specifications to agent questions. As was described in section 3.3.4, agent questions referred to different risk dimensions and privacy classes that were used in the current analysis to determine a modification quota per question category (see also Appendix B3):

$$MQ_R = \left(\sum_{i=1}^{n_p} (M_i^{pR} \div Q_i^p) \right) \div I^p \quad \text{with}$$

MQ_R [39]= Average modification quota to be found in a question category *R*, where *R* refers to a bundle of questions addressing either functional (fun), financial (fin), social (soc) or psychological (psy) risk or where *R* refers to a bundle of questions that represent different privacy classes such as non-private questions relating directly to the product (pd), marginally private question indirectly referring to the product (pepr), purely personal questions (peip) or finally relatively private questions concerned with product usage (u)

M_i^{pR} = Number of modifications made in one question category *R* by an individual *i* searching for a product *p*

Q_i^p = Number of questions encountered by an individual *i* in a category *R* for a product p.

I^p = Number of individuals who shopped for product *p* and made modifications to any of the categories

The median of modifications made per product category (M) (see table 9) shows that jacket shoppers who modified agent options did so only slightly more often than their camera counterparts although this finding is not significant. This finding corresponds

[39] M_i^{pR} is divided through the number of questions in a category (Q_i) in order to take account of the fact that the different question types (pd, pepr, peip, u or fin, func, psy, soc) were not distributed equally in the two store versions.

to the fact that jacket shoppers also perceived slightly higher levels of uncertainty connected to their purchase.

Looking in more detail into the type of modifications made it turned out that in line with cameras' higher levels of inherent financial risk, shoppers for this product category also adjusted more often the agent's price parameters available in the search engine. More precisely, the data revealed that about 11% of camera shoppers adjusted the price range in which they wished to buy at least once while subjects searching for a jacket had in general a relatively firmer idea of what they wanted to spend (only 5% changed the price range once at a maximum).

Another finding that suggests perceived purchase risk to be in line with risk reduction behavior is the construct of psychological risk. Jacket shoppers modified significantly more agent questions that addressed this risk construct which was particularly relevant for jackets. Surprisingly, however, this type of consistent behavior could not be observed for the sociological risk dimension. Obviously, camera buyers did feel a need to modify just as many agent questions concerning 'social acceptance' of their product than jacket shoppers did (which is not in line with the level of sociological risk measured in advance of the shopping sessions).

Besides this comparison of perceived risk dimensions inherent in a product with subsequent attempts to address them during the information search process, it was also important to see what type of agent questions users would find important for product selection. Here the data suggest that consistent with the experience characteristic of apparels, jacket shoppers made significantly more modifications to usage related agent questions than camera shoppers did. In general, looking at the relative number of modifications made to personal and usage related questions, jacket shoppers seem to have put more emphasis on these relatively private issues of purchase than camera shoppers. Jacket shoppers were also significantly more willing to respond to private issues in the purchase context ("peip-questions"). Seen that usage related and personal questions were rated as rather illegitimate and unimportant in the independent study conducted (see section 6.2.3.2. for analysis and Appendix C, table C1 for data), the modification quotas could suggest that users allow for more insights into their private lives when product nature justifies this. More research is, of course, needed to confirm this preliminary evidence.

5.4 Discussion of Results for Online Marketing

The measured perception of products confirmed that participants felt slightly more uncertain in judging the quality of winter jackets prior to purchase. Jackets for the purpose of this study can therefore be regarded as a representative experience good. However, against expectations, the level of overall perceived risk was not significantly higher for jackets than for cameras. Therefore, the observed superior levels of interaction for winter jackets can not be attributed to the absolute amount of perceived risk prior to purchase (OPR). Instead, they seem to be more attributable to the 'experience' nature of the product, and the concurrent need of users to extensively inspect and visualize all product alternatives on offer (i.e., trying to anticipate the experience).

Clear support was rendered by the findings for the argument that consumers have distinct navigational needs when they search for different products online. In fact, today's electronic commerce environments display a strong lack of product context recognition. Not only do they often fail to support users effectively in their decision making process [Spiekermann and Parachiv, 2001], but site design and interactive functionalities also tend to follow an approach of 'one-size-fits all' for most product categories: Information provision is not always adjusted to those product attributes and features that might be of particular concern to customers. Usually, the same type of information is displayed no matter which product the online customer came for. Dialogue-systems strongly focus on product attributes only, but in general do not correspond to consumers' softer purchase concerns. Finally, detailed product representation, product description or visualization, are mostly identical in a domain for all goods on offer. The findings presented in this chapter show the necessity for online marketers to respect product nature more explicitly in the design of web sites. More specifically, the results include some hints for the design of agent dialogue design as well as context adjusted representation of products.

5.4.1 Product Related Focus of Dialogue Systems

It was shown that customers associate different types of purchase risk with the products they seek. In the current study, cameras were associated with a relatively higher functional and financial risk while jacket shoppers felt the socio-psychological side of the product to be relatively more important. In line with these product perceptions, camera shoppers also modified relatively more functional and financially related preferences. Considering the modification quota for questions with a socio-psychological focus jacket shoppers, in contrast, put significantly more focus on the appropriateness of these variables. As a result, some evidence is given to the argument that dialogue systems could be enhanced if they respected the risk dimensions inherent in a product [Spiekermann and Parachiv, 2001].

At the same time, it was interesting to see that jacket shoppers also put a relatively strong weight onto the modification of functional product attributes. This is surprising given that the relatively small stated risk perception on this dimension prior to purchase. However, given this finding, marketers offering a differentiated dialogue along risk dimensions might also be able to observe the 'true concerns' of their customers in this way. Seeing that users put weight on the specification of specific product attributes corresponding to particular types of product risk, marketers could learn about the true drivers of the purchase decision-making process and adjust risk-reducing dialogue-systems accordingly.

Finally, the results suggest that dialogue-systems can be relatively detailed and lengthy. Not only did online users specify many product attributes when they were involved in a high-involvement purchase (see the surprisingly big share of agent questions answered and additional modification rate), but they even displayed a readiness to adjust softer and more personal variables addressed by the agent. Even though the time manipulation of the experimental set-up might have led participants to browse and answer more questions than they would usually correspond to in 'real-world' online stores, this finding is important for two reasons: Firstly, the high level of disclosure suggests that people do not value their privacy as much as current household surveys often suggest. Second, lengthy dialogues do not seem to lead to customer annoyance or a loss of trust. In contrast, 77% of the users expressed satisfaction or even high satisfaction with the search engine and many underlined their positive experience by written remarks in the debriefing questionnaire stating that they had perceived the system to be extremely "user friendly", that they had felt "personally addressed" and "well guided". This is surprising, as that the agent dialogue involved an extremely exaggerated detail of product specification including many highly personal questions. All in all, the results suggest that there is a lot of room in dialogue-systems to exchange information with consumers without inducing a feeling of privacy intrusion among them.

5.4.2 Context Adjusted Representation of Products

During the observed shopping sessions, jacket shoppers displayed a significantly higher interest in the detailed and manually controlled inspection of products than camera shoppers did. They wished to view many more products and had a stronger need for visualization (photo enlargements). At the same time, the inspection of fact sheets seem to have had less importance for this group of buyers. In contrast, camera shoppers viewed much less products, but attributed a lot more attention to detailed information on each object (time per product). The results suggest that online consumers appreciate a differentiated way in which products are presented: while for some products, for which appearance is important, the investment might be worthwhile to present them with a strong visual focus employing interface technology that allows to view, enlarge and turn the product, these interface capabilities might not be necessary for buyers of search goods. In contrast, search goods that can be well described on the basis of plain product attributes and factual criteria may be better represented if the web site allowed for an objective inspection of product details in the form of fact sheets and comparison matrices. More research would be needed to confirm this finding.

5.5 Conclusion

All in all, the comparative analysis of search behavior for winter jackets and compact cameras suggests that higher levels of uncertainty in product judgement lead to more manual search. At the same time, relative importance of the agent is reduced. This finding is roughly in line with what was expected on the basis of equation model results presented in chapter 4 and it suggests that agents are not equally important for all electronic commerce purchase environments. However, search behavior was only investigated for two products, compact cameras and winter jackets. More research would be needed if the current findings were to be generalized.

Finally, the hypothesis derived from the structural equation model that OPR leads to more product inspection versus the use of an agent could not be confirmed on the basis of the current data set, as different levels of OPR were not able to be measured for the two products under study. More research would therefore be needed here as well. Doing so, particular emphasis would have to be put on the selection process of experimental participants in order to avoid the same self-selection problems that were encountered in the experiment.

Chapter 6

6 Consumer Privacy Concerns in Interacting with Agents

6.1 Introduction to Privacy Issues in Online Interactions

A number of researchers in agent technology have pointed at the privacy issue as a central factor for agent acceptance by users [Shearin, 2000; West et al., 2000, Norman, 1994]. Norman, for example, stated: *"Privacy and confidentiality of actions will be among the major issues confronting the use of intelligent agents in our future of a fully interconnected, fully communicating society"* [Norman, 1994, p.70]. The belief of academics in online privacy as a major design issue and potential impediment to agent use is founded on household surveys that confirmed peoples' concern to maintain privacy online [Pew Internet & American Life Project, 2000; Ackerman et al., 1999; Hoffman et al., 1999]. Many scholars have also presented evidence that online users wish to have control over the data they leave behind in electronic environments [Shearin and Maes, 2000, Hoffman et al. 1999]. In addition, privacy or 'the right to be let alone' has historically been considered as a fundamental right of people [Warren and Brandeis, 1890] and found entry into countries' legal systems.[40]

On the other hand, customer information has become a strategic asset for companies, which allows them to leverage the benefits of one-to-one marketing practices [Kenny and Marshall, 2000; Reichheld and Schefter, 2000]. As a result, companies have an interest in creating personal profiles on their customers and web site visitors. Many Internet business models are built on customer information as a major asset and some online services even offer "freebies" or other incentives in exchange for customer information [Chang et al., 1999, p.85].

[40] See e.g. European Directive 95/46/EC of the European Parliament and of the Council of 24 October 1995 on the protection of individuals with regard to the processing of personal data and on the free movement of such data. Also, the 'Recht auf Informationelle Selbstbestimmung' which is part of the German 'Grundgesetz' recognizes privacy as a fundamental right of people (here it falls among the 'Allgemeinen Persönlichkeitsrechte' Art. 1 Abs. 1 GG).

Given these apparently conflicting interests of online marketers and consumers, Hagel and Rayport already noted in 1997, that there will be a *"coming battle for customer information"* [p.53] and it is yet unclear how it will be resolved. One important question in this battle will certainly be to understand how valuable private information really is to consumers. Most privacy surveys conducted so far have been uniquely based on people describing their general attitudes towards the subject [Pew Internet & American Life Project, 2000; Ackerman et al., 1999; Westin, 1996]. Few insights have been gained though on the way consumers actually behave online. Some studies suggest that people are willing to give away private information for appropriate returns [Hagel and Rayport, 1997, Chang, 1999]. Other studies on social factors in human-computer interaction have shown that people often treat computers as they treat other human beings [Moon, 1998; Nass et al., 1995] and as a result can be led to disclose a lot about themselves if the machine responds appropriately [Moon, 2000].

Are online users/consumers really as concerned about their privacy as is widely believed? How do they value their private information? And how do online users deal with their privacy when they get the benefit of high-value personalized product recommendation in exchange? These questions are important to comprehend the role of privacy in agent interactions.

The shopping experiment was ideal to investigate these questions. Firstly, there was the possibility of measuring not only privacy concerns, but actual behavior. Second, participants were put in a second-generation-electronic-commerce type of environment where they would receive a benefit for data revelation: a personalized agent recommendation. Against this background, it was investigated to what extent are stated privacy concerns and preferences really impediments to agent interaction. So doing, it was assumed that agents are operated by marketers (web site hosts) and consequently, profile ownership does not remain with the customer.

6.2 Measuring Disclosure in Human-Agent Interaction

During the shopping session, agent Luci gave participants the opportunity to answer 56 purchase related questions. Seen that a successful offline purchase process was shown to involve only 3,3 questions that are discussed between a human sales agent and a customer [Haas, 2001], it was expected that the volume of 56 agent questions would not be fully exhausted by most of the experimental participants. Moreover, it was believed that the degree of privacy concern would be reflected in the number of agent questions answered by participants.

However, taking only the number of agent questions answered as a measure for the degree of participants' disclosure would have had one major drawback: it would have assumed that all information revealed by shoppers to be of the same value to them. Thus, answers would have been valued irrespectively of their importance and legitimacy .

In order to avoid this simplifying way of measuring disclosure and to respect more of a participants' perceived revelation during the shopping session, it was decided to develop a new measure. This measure aims to approximate the degree of perceived self-disclosure observable in human-agent interaction. What has been missing from research up to now though is an insight though into the very way in which people evaluate their private data. As Hine and Eve stated in 1998 [p.253]: *"Despite the wide range of interests in privacy as a topic, we have little idea of the ways in which people in their ordinary lives conceive of privacy and their reactions to the collection and use of personal information."*

Studies that have explored the phenomenon of private information revelation online have done so focusing solely on the provision of single data units (such as the provision of an e-mail address), but reflected little on the context in which information units are requested on the Internet (see e.g. [Ackerman et al., 1999]). However, as Badenoch et al. [1994] resume, the *"value [of information] is almost entirely dependent on the specific circumstances in which the information will be used"* [p.24]. A central aspect of information valuation in our model is therefore the context in which information is given. Context has been recognized for long in information science literature as one of the most determining factors to value an information unit [Badenoch et al., 1994; Hine and Eve, 1998]. For example, in one context users might perceive the provision of their telephone number as a necessity and are therefore most willing to give it away (no/little cost). In other contexts, they might regard the provision of the telephone number as an unnecessary intrusion into their privacy and will only reluctantly provide it (high cost).

Since classical information search analysis is often based on a cost–benefit tradeoff (made by actors when determining behavior) [Moorthy et al., 1997; Stigler, 1961], the idea that online consumers incur a cost of search when interacting with agents was introduced. We called this cost ‘private consumer information cost’ (PCIC) [Annacker et al., 2001]. It is perceived by consumers when revealing truthful information about themselves on the Internet while knowing that afterwards some parts of their identity and personal profile will be known to the organization hosting a site (and expecting that their data will probably be used for further analysis or for sale).

The challenge confronted in developing a model for this construct of private information cost was that no tangible value is actually capable of representing it appropriately. There is usually no cost created to produce private information. Economic freebies or services so far offered in exchange for PCIC strongly differ in value [Chang et al., 1999]. Our model therefore focuses more on the identification of some overall variables driving PCIC and their interrelations. It can serve as an approximation for the likely perception of an information request that could be made by an online agent.

6.2.1 Independent Variables Driving Personal Information Cost on the Internet

PCIC has been developed against the background of disclosure to a selected-option based dialogue systems. Personal consumer information cost (PCIC) stands for the loss in utility a consumer perceives when giving away a truthful information unit about himself to such a system, hosted by a third party. This third party is an entity with which the consumer has no personal relations and for which high levels of trust have not been established. An example of such a third party could be the host of a web site. PCIC expresses itself in a consumer's reluctance to answer the question of an interface agent in the context of an online search process for products. Strong reluctance stands for high information cost. In contrast, if a user has no problem to reveal an information unit about himself he incurs little cost.

As the determination of PCIC means to attribute value to different types of information units, research in information theory provided a starting point for modeling. Considerable research has been done on the valuation of information in management science (see [Badenoch et al. 1994, p.59] for an overview). None of these approaches are directly transferable to the current context. This is, because traditional theories of information value have a different perspective on value creation: While they are concerned mostly with the benefits for the recipient of information compared to the production cost of this benefit, the current context relates more to the cost of the provision of an additional unit of personal information while at the same time this provision leads to no measurable production cost. Yet, some principal theoretical constructs of information valuation can still be transferred to the current context, notably the influence of the context on information value, the relevance the information unit holds in this context and the effort required to process it [Badenoch et al., 1994].

The context in which an information unit is demanded can influence the perception of PCIC. A practical example may illustrate this: Let's assume a buyer who wants his goods to be delivered to the home. He will probably be most open to provide his address to the supplier. The delivery context creates the necessity to provide the address and thus legitimizes its provision. If, in contrast, the customer picked up the ordered products himself, he would probably be surprised if he had to leave his address with the vendor for there is no obvious contextual need for this information provision. It is likely that he would be reluctant to provide it. The example shows that the perceived legitimacy of an information request in a specific context drives the perceived cost of providing it. As Hine and Eve put it [1998, p.257]: *"Requests for information not deemed necessary in order to carry out this function were deemed intrusive."* The arguments suggest that the perceived legitimacy of a question in the disclosure context influences PCIC. Perceived question legitimacy therefore represents one dimension in the PCIC evaluation model that has been developed. It is defined as the degree to which a question is perceived as justified in a given context.

The legitimacy of an information request is not only determined by the context, but also by its importance in that context. In the above example, providing the delivery address is very important for the fulfillment of the service. It is therefore intuitive to argue that the buyer perceives little cost to provide it. Yet, there may be other legitimate information units in the delivery context which are less important and thus are perceived more costly to provide. For example, the telephone number of the product recipient, or his working hours. The perceived importance of an information unit in a specific context thus also has an impact on the perception of PCIC. For modeling purposes, importance is defined as the perceived degree to which an information request can contribute to an optimal product or service experience. At the same time, while importance drives the legitimacy of an information request, the opposite does not hold true. For example, asking the buyer of a winter jacket what type and color of buttons he prefers may be a legitimate question in the purchase context, but will probably not be important to most consumers.

Finally, it has been recognized in literature that the effort to process information also leads to cost for consumers [Bettman, 1979]. Eventually, there may be information requests online that are difficult for users to answer. As a result, they may be reluctant to do so. For example, if a shopping agent asked for the envisaged gigabyte size of a hard disc, but the user does not know what a hard disc is. The perceived difficulty in answering a question represents the third dimension of the PCIC evaluation model that has been proposed.

The three main drivers of PCIC, identified as perceived legitimacy, importance and difficulty to provide an information unit in a specific online sales context are summarized in Figure 8. They are at the core of the empirical investigations presented hereafter. Certainly, they are not able to explain the phenomenon of PCIC in its entirety. Individual differences, for example, in the individual level of trust in online providers, online privacy attitudes, product experience etc. may also drive the level of PCIC. Yet, as will be shown below, the three variables examined represent a good starting point to capture online users disclosure concerns in online purchase situations.

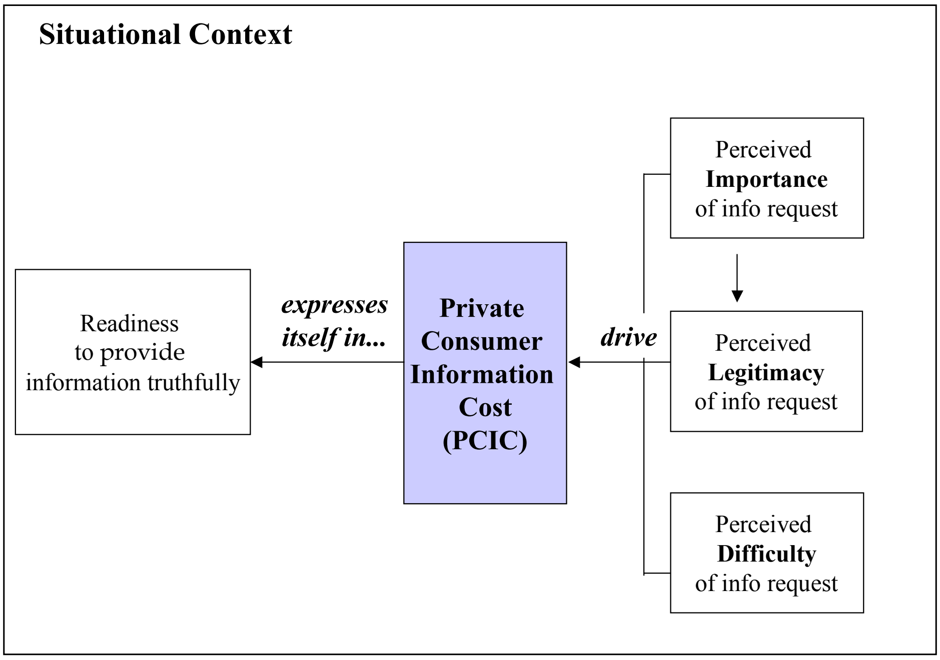


Abbildung 8: Drivers of Personal Consumer Information Cost (PCIC)

6.2.2 Empirical Survey Design

In order to investigate the hypothesized drivers of PCIC, an empirical survey was conducted on how the request for different information units would drive consumers' perception of PCIC. 39 subjects were invited to the university laboratory at Humboldt University Berlin and were asked to judge the 112 agent questions employed by the electronic shopping agent Luci (56 questions per product).[41]

The 112 agent questions and multiple choice answer options were displayed one by one to subjects on the left side of a computer screen. Subjects were asked to imagine that the questions displayed to them would be asked by an electronic shopping agent

[41] Note that these 39 subjects did not know anything of the shopping experiment and also did not participate in it.

on the Internet in the context of a purchase process for either winter jackets or compact cameras. On the right side of the screen, 11-point scales (ranging from 0 to 10) simultaneously asked subjects to judge each question's legitimacy and importance in the sales context, the difficulty to answer it as well as the overall perceived information cost (for a screenshot of the rating tool used see Appendix B6). The construct of information cost was explained to the participants in advance of the rating sessions through a text based briefing which used the following definition of PCIC: Information Cost is standing here for the 'intuitive readiness' to truthfully answer the question of the search engine; thus the spontaneous feeling, whether you would be willing to reveal the demanded information about yourself. 'No' Information Cost would mean that you have no problem at all to answer the question truthfully. 'Very high' Information Cost stands for the emotion that under no circumstances you would give this type of information about yourself to a search engine (for the full details of participant briefing see Appendix A6).

6.2.3 A Model for Personal Consumer Information Cost (PCIC)

For modeling purposes one outlier had to be excluded from the initial number of 39 observations. The model presented hereafter is therefore based on 38 observations.

6.2.3.1 Initial Regression Analysis

The relationship between PCIC as the dependent variable and legitimacy (*Leg*), importance (*Imp*), and difficulty (*Diff*) as independent variables were initially expressed as:

$$PCIC_{ij} = \beta_0 + \beta_1 Leg_{ij} + \beta_2 Imp_{ij} + \beta_3 Diff_{ij} + \varepsilon_{ij}, \tag{1}$$

where: $i = 1, \dots, I$ number of respondents, $j = 1, \dots, J$ number of questions.

As ordinary least square analysis of this model (1) resulted in a relatively low R^2 of .439 for pooled data, $F(3, 4252) = 1108.69$, $p < .01$, an alternative model was estimated where unobserved heterogeneity was captured by dummy variables for each respondent (table 10).

Tabelle 10: Results for an Initial Fixed Effects Regression Model for the Evaluation of PCIC:

Overall model fit		
$R^2 = .623$		
Adj. $R^2 = .619$		
F(40, 4215) = 173.80, p < .01		
Parameter estimates		
Independent variables	**Parameter**	**Dependant variable: PCIC**
Intercept	β_0	6.252
Leg	β_1	-.559 (.017) ***
Imp	β_2	-.011 (.018)
Diff	β_3	.138 (.014) ***

( ) standard error; *** p < .01

Since the data consists of partially dependent observations, controlling for these dependencies might lead to slightly lower levels of significance.

As can be seen from table 10, model (1) fit was considerable improved through the respect of individual differences in question judgment. The signs of all parameters supported the expectation that legitimacy and importance lead to a reduction in PCIC while the difficulty of an information request influences it positively. Surprisingly, however, the impact of perceived question importance turned out to be not significant. Investigating this result in more detail, a typical case of co-linearity was discovered in the data with a bivariate correlation of .825 between *Leg* and *Imp.* Co-linearity diagnostics suggested a borderline case of co-linearity with the largest condition index (18.50) being above 15 (see [Belsley et al. 1980]) for more details on this type of problem)

One way to address the problem of co-linearity in regression analysis is to formalize the relationship between the two related variables [Darnell, 1995]. It was therefore decided to explore the relationship between *Leg* and *Imp* in more detail (figure 9) in order to be able to comprehend the relationship between these two variables.

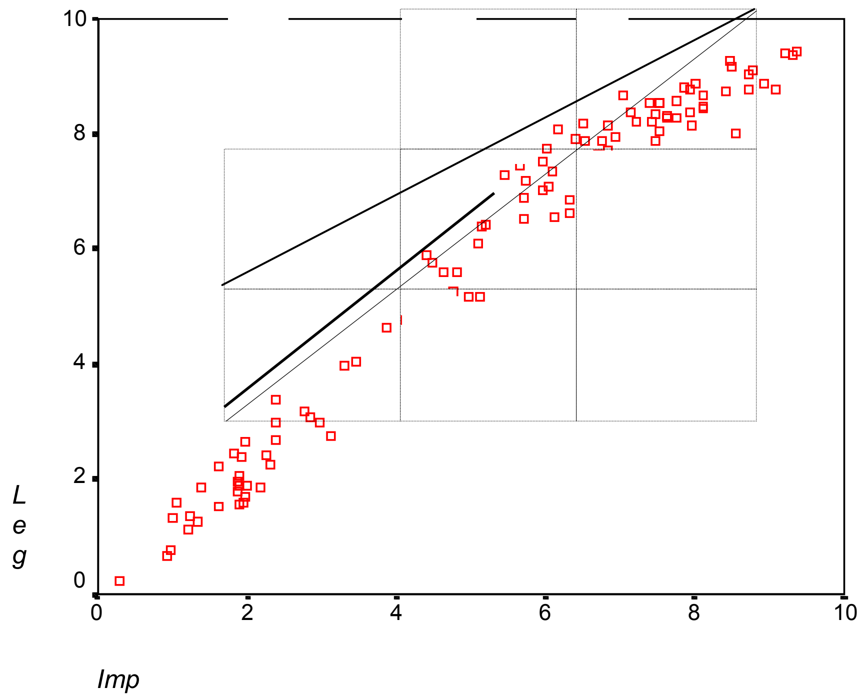


Abbildung 9: Relationship between Mean Perceived Legitimacy and Importance of Agent Questions

6.2.3.2 Relationship between Legitimacy and Importance of Information Requests

In order to allow for better interpretation of the data and visualize the relationship between perceived legitimacy and importance the data was aggregated by computing mean values of both variables (*Leg* and *Imp*) for all questions across the 38 subjects. Figure 9 gives an overview of the observations made. The graphical presentation of the data suggests that besides a strongly apparent linear relationship between legitimacy and importance of interface questions, mean judgments can apparently be separated into two distinct groups: For questions in the lower left corner (represented by graph B) an increase of one scale point in importance seems to correspond to a similar increase in legitimacy. In contrast, for questions in the upper right corner the increase in legitimacy is noticeably smaller (graph A).

In order to analyze the nature of these two apparently distinct relationships, the question nature was included within the project's interpretations. As was discussed in section 3.3.4. questions were purposefully designed to represent four different categories (for more detail see Appendix B5): 1) *non-private questions* (pd) addressing specific attributes sought in the product (e.g.: How resistant do you want the fabric of *the* jacket to be?), 2) *marginally private questions* (pepr) that referred to the consumer in person, but were also closely linked to product choice (e.g.: How important is the resistance of the fabric of *jackets* to you?) 3) *relatively private questions* (u) looking into the usage envisaged with the product (e.g.: Where do you want to wear the jacket?) and 4) *purely private questions* (peip) that would somehow be related to the sales context, but be completely irrelevant for product choice. (e.g. : Where do you obtain your knowledge about fashion? in the purchase context for jackets). Transferring this typology to the two distinct graphs (A and B), it is interesting to note that group A of questions (represented by graph A) are primarily product related questions (*pd*) as well as person oriented questions with a product focus (*pepr*). At the same time, group B (represented by graph B) are mostly questions focusing on personal attributes (*peip*) or usage (*u*). This finding suggests that the legitimacy of a product related question (A) may be less driven by its importance than this is the case for a more personal question. Or else: It seems that the legitimacy of personal agent questions may be relatively stronger driven by their perceived importance in the purchase context.

To go into more detail, *Leg* and *Imp* scales were divided into three tercile sections (0 – 3.33, 3.34 – 6.66, 6.67 – 10) and created 9 different classes for *Leg* x *Imp*. As can be seen in figure 9, there are only 5 classes relevant to the analysis: class 7 containing questions of low legitimacy and importance, classes 2 and 3 containing in contrast highly legitimate and important questions and class 5 where legitimacy and importance are medium. Class 4, which only contains two items appears negligible for the discussion. Table 11 gives an overview of how the 4 question classes (pd, pepr, u, peip) relate to the perceived legitimacy and importance frame in figure 9. There are strong scientific limitations of this table as some of the cross-tabulation categories contain a very small number of observations. However, the table still provides some valuable insights and hints for future research on this subject which is why it was included within the analysis.

Tabelle 11 Relating Nature of Agent Questions to Leg x Imp Classes:

			Shopping Agent Question Types				Total
			Pd	Peip	Pepr	U	
Leg x Imp Classes	2	Count	14		3	1	18
		% within cat	33,3%		13,0%	7,7%	16,1%
		% of Total	12,5%		2,7%	,9%	16,1%
	3	Count	26		13	2	41
		% within cat	61,9%		56,5%	15,4%	36,6%
		% of Total	23,2%		11,6%	1,8%	36,6%
	4	Count		1		1	2
		% within cat		2,9%		7,7%	1,8%
		% of Total		,9%		,9%	1,8%
	5	Count	2	5	7	6	20
		% within cat	4,8%	14,7%	30,4%	46,2%	17,9%
		% of Total	1,8%	4,5%	6,3%	5,4%	17,9%
	7	Count		28		3	31
		% within cat		82,4%		23,1%	27,7%
		% of Total		25,0%		2,7%	27,7%
Total		Count	42	34	23	13	112
		% within cat	100,0	100,0	100,0	100,0	100,0
		% of Total	37,5%	30,4%	20,5%	11,6%	100,0

As would be expected, 95,2% of product attribute questions (*pd*) were perceived as highly legitimate by subjects while over 82,4% of solely person oriented questions (*peip*) were perceived as little legitimate and unimportant. Highly legitimate product questions were spread across classes 2 and 3. Analyzing their nature in more detail showed that class 2 questions are asking for product attributes that might be less important to customers in the product choice process (such as the question asking for the type of hood on the jacket or the carrier cord of the camera) while questions in class 3 address product attributes with more choice relevance (such as color and material of the jacket or weight and zoom of the camera).

Looking into the perception of person oriented questions (*peip*) it is not surprising to note that people attribute little legitimacy and importance to those questions that only focus on the individual and obviously do not contribute to product or service delivery. As a result, it could be argued that asking for age, address, hobbies or other information on web site (e.g. through online questionnaires) may not be welcomed by users if there is no reason for it or no context relation to the host's activities. This may be one explanation for people telling lies online when being asked, out of nowhere, to provide demographic data [Grimm et al., 2000; Sheehan and Hoy, 1999]. More research may be useful to confirm this possible finding.

On the other hand, table 11 indicates a relatively high acceptance (56,5%) of questions that, albeit focusing on the person do have a connection with product selection (*pepr*-questions). This implies that customers in many cases do not feel annoyed if they are asked personal questions as long as these relate to the product context. In fact, none of the *pepr*-questions have been perceived as totally illegitimate or unimportant. The same is true for usage related questions: those that relate somehow to features of the product (like motives you want to capture with the camera) are perceived as sufficiently important and legitimate (class 5). On the other hand, those that lack a link to product selection are perceived as rather illegitimate and unimportant.

6.2.3.3 Final Definition of Overall Model

Formal co-linearity diagnostics as well as the strong linear relationship between *Leg* and *Imp* depicted in figure 9 led to the conclusion that the validity of results obtained for the original fixed effects model (1) might be questionable. The model was therefore re-specified and estimated as a simultaneous equation model (2), which solved the problem of co-linearity. More precisely, the relationship observed for *Leg* and *Imp* was specified. Thus, in addition to the direct effects of *Leg*, *Imp* and *Diff* on *PCIC* a linear relationship between *Leg* and *Imp* was included (for detailed model output see Appendix C, table C3).

$$\begin{aligned} PCIC_{ij} &= \beta_0^{IC} + \beta_1^{IC} Leg_{ij} + \beta_2^{IC} Imp_{ij} + \beta_3^{IC} Diff_{ij} + \varepsilon_{ij}^{IC}, \\ Leg_{ij} &= \beta_0^{Leg} + \beta_1^{Leg} Imp_{ij} + \varepsilon_{ij}^{Leg}. \end{aligned} \tag{2}$$

Again dummy variables were used to control for individual differences. As was shown above in the graphical analysis, a clear difference exists in the perceived relation of legitimacy and importance for the two question groups A and B. Based on model (2) two group-specific models were therefore estimated in addition to one representing the total sample. Maximum Likelihood estimates for the model parameters (table 12) have been generated by M*plus* [Muthén and Muthén, 1998], a software for the estimation of mean- and covariance structure models (widely known as SEM). Because of the small number of respondents one might be tempted to reject the application of this methodology in our study. To put this objection into perspective the following facts should, however, be taken into consideration. First, although sample size is 38 the number of observations is much higher since multiple data (112 questions) was collected for each respondent. This results in a total sample size of 4,256 observations. Secondly, the analysis does not correspond to typical SEM applications where latent variables with multiple indicators are involved. It is therefore questionable if general minimum sample size recommendations (100 - 200) or rules of thumb developed for these more complex models are applicable to the present study. Third, the ratio of sample size (4,256) to number of free parameters (82) is 52:1, which is considerably above recommended ratios to obtain valid parameter estimates and standard errors (see e.g. [Bentler and Chou, 1987]).

Since model (2) has one degree of freedom in addition to the multiple correlation coefficient $\hat{R}^2$,alternative overall fit measures for covariance structure analysis have been used (for the interpretation of these fit statistics see for example [Jöreskog, 1993]). As can be seen from table 12, results for the total sample as well as for group A show an excellent fit according to the RMSEA fit indicator [Browne and Cudeck, 1993, Hu and Bentler, 1999]. However, it should be respected that in cases of low degrees of freedom (such as ours), fit statistics have relatively less confirmation power [MacCallum et al., 1996]. This moderates the confirmation of model fit slightly. It may be mirrored also in the wide confidence intervals that can be observed with the RMSEA measures in both cases. In addition, results for group B represent a borderline case in model fit as indicated by a fairly high RMSEA of .070.

Tabelle 12 Results for a Final Simultaneous Equation Model with Fixed Effects for the Evaluation of PCIC:

Overall model fit		
Total sample	**Group A**	**Group B**
$\chi^2_{(1)} = 1.86$	$\chi^2_{(1)} = 4.34$	$\chi^2_{(1)} = 9.74$
RMSEA = .014	RMSEA = .037	RMSEA = .070
RMSEA 90% CI (.000,	RMSEA 90% CI (.007, .075)	RMSEA 90% CI (.035, .113)
$\hat{R}^2_{IC} = .622$ $\hat{R}^2_{Leg} = .739$	$\hat{R}^2_{IC} = .481$ $\hat{R}^2_{Leg} = .594$	$\hat{R}^2_{IC} = .693$ $\hat{R}^2_{Leg} = .735$

Parameter Estimates				
		Total Sample	Group A	Group B
Explanatory variables	Parameter	Dependent variable: PCIC		
Intercept	β_0^{IC}	6.250	4.569	6.274
Leg		-.559 (.017) ***	-.397 (.022) ***	-.457 (.027) ***
Imp	β_2^{IC}	Direct effect		
		-.010 (.017)	.003 (.019)	-.055 (.029) *
		Total effect		
		-.499	-.232	-.437
Diff		.138 (.014) ***	.182 (.016) ***	.159 (.020) ***
		Dependent variable: Leg		
Intercept	β_0^{LEG}	1.289	3.737	.714
Imp		.875 (.009) ***	.591 (.013) ***	.839 (.015) ***
( ) standard error; ***p < .01; *p < .10; since the data consists of partially dependent observations, controlling for these dependencies might lead to slightly lower levels of significance.				

Comparing model coefficients for the total sample model (2) (table 12) and our initial model (1) (table 11) clearly shows that the effect of *Imp* on PCIC was considerably underestimated by the original single-equation fixed effects model (1). Although the direct effect (-.010) is still insignificant in model (2), the total effect (-.499) is quite large and only moderately smaller than the effect legitimacy has on PCIC (-.559). The impact of perceived importance on information costs is thus obviously predominantly mediated by its influence on perceived legitimacy.

Since the two group-specific models A and B display some significant differences they were interpreted in more detail: Just as for the total sample the most important driver of PCIC in both groups is the perceived legitimacy of an information request. *Imp* drives PCIC predominantly via its influence on *Leg*. However, for more person-related questions (group B) a small direct effect could be discerned. As might have been expected from the preceding analysis of the *Leg*-*Imp* relationship (figure 9), *Imp* has thus a much stronger influence on *Leg* in group B (more personal questions) than in group A. Likewise the effect of *Leg* on PCIC is stronger in group B. Compared with the direct effect of *Leg* and the total effect of *Imp* on PCIC, the difficulty to answer a question is obviously perceived as less costly by respondents. As far as *Diff* is concerned, there are also only minor differences between the two groups.

6.2.4 Discussion of Results

With the development of the PCIC index a measure has been developed that to a certain extend reflects a user's perception of self-disclosure when being asked for information online by an interactive agent. More precisely, it was shown how the perceived legitimacy, importance and difficulty of an agent question combine to create in online users a feeling of intuitive readiness or denial to truthfully respond to a dialogue system.

With this, a model has been created that may be used for the strategic design of agent interfaces suggesting that agents should watch out for the perceived legitimacy and importance of their information requests in the purchase context. Today, most electronic commerce web site are only asking users for desired product attributes (pd) (e.g. product configuration engines on manufacturers sites or product search engines on infomediary sites) or they ask them to fill out lengthy online questionnaires which mostly contain personal questions (peip). Very few sites start to include questions on usage (u) and nobody is communicating with users yet on general product expectations (pepr) (see critical discussion of current agents in [Spiekermann and Parachiv, 2001]). As was shown above, however, users do accept personal questions as long as they relate to the product context (pepr-questions). For example, asking a consumer whether he prefers trend models when choosing a jacket is initially a personal question, because it contains information on the consumer's general attitude towards fashion. As such it has considerable value for sellers, because they directly learn about their buyer's preference. However, the information unit also serves directly to recommend the right type of product to the client by respecting the degree of trendiness of different models in the electronic choice process. Strictly speaking, most marketers therefore realize opportunity cost of information today if they do not take advantage of the potential knowledge accumulation they can realize with pepr-questions. Additionally, as can be seen from graph A in figure 9, *pepr*- as well as *pdd*-questions are less driven by the *Imp* factor than personal- or usage oriented questions (graph B has a steeper slope than graph A). This finding implies that as questions become slightly less important for the customer, their legitimacy is not decreased to the same extend. Taking advantage of this relationship means that marketers could ask customers *pdd*- or *pepr*-questions that even though less relevant to the buyer are still important for product enhancement purposes. For example, asking consumers what type of closing mechanism they prefer for compact cameras might not be too relevant a question for most buyers. Yet, for manufacturers of compact cameras this information is highly valuable for product design decisions.

While these arguments suggest that there is room for online marketers to use dialogue-systems as an effective means to collect consumer information, the questions remains whether online users' privacy concerns will not impede an extensive collection of data. As was outlined above, privacy concerns are widely believed to potentially impede extensive online interaction. The next sections of this chapter will explore whether this belief is justified.

6.3 Privacy Preferences Versus Actual Interaction Behavior

On the basis of answering ratios measured for the agent dialogue in chapter 5 (table 9) it was clear that experimental participants had, in fact, disclosed much more information about themselves to the shopping agent than initially expected. However, this openness could have been attributable to corresponding low levels of low privacy concern in the sample. As a result, the starting point of the privacy analysis was the measurement of privacy attitudes in the sample. These attitudes would then be contrasted with behavior.

6.3.1 Data Used for the Analysis

The data used to investigate privacy attitudes and behavior were taken from treatments 1 through 4. Thus, data from camera and jacket shoppers have been analysed simultaneously. As 6 of the 206 individual observations had missing data, analysis was based on 200 observations. Another group of 29 subjects was identified who did not see and consequently did not consciously answer or reject several agent questions. As this behavior could not be explained and as it could not be attributed to any privacy concerns, these subjects were excluded from analysis leading to a final dataset of 171 observations. Two data sources were used for analysis: questionnaire answers to discern privacy preferences and log files to analyse behavior.

6.3.2 Measurement of Privacy Attitudes through Cluster Analysis

To investigate privacy attitudes, this project built on earlier work by Ackermann et al. [1999]. Parts of a questionnaire were used that has been developed by this group of scholars to test privacy preferences. More precisely, 14 variables were used to derive participant's privacy attitudes. 10 variables related to the readiness of subjects to reveal specific data units (such as e-mail address, name, hobbies or credit card number). 3 variables were indices developed on the basis of different online scenarios, for which users indicated how they would behave in terms of data revelation. And one variable finally referred to the question whether participants feared to sacrifice their privacy online. Appendix C, table C4 gives a detailed overview over the measures used. All data were z-transformed for the analysis.

With the help of the SPSS software package a K-means cluster analysis [Bühl and Zöfel, 2000; Jain et al., 1999] was then conducted. In order to use K-means, it has often been pointed out that data needs to be based on interval scales [Stevens, 1946]. However, if equal distance between answer options can be assumed, which is the case for the current analysis, ordinal scales can equally be used in K-means analyses. As Traylor concluded [Traylor, 1983]: *"Ordinal data can, in many circumstances, be treated as interval data without a great loss in accuracy and with a great gain in interpretability"*.

An initial hierarchical clustering process based on squared Euclidian distances had indicated the existence of four distinct clusters in the data (for more detail, see agglomorative schedule in Appendix C, table C5). Based on this target number of four clusters, K-means analysis was then conducted, starting out with a differentiated view on camera and jacket shoppers.

The differentiated analysis for the two product groups showed that the four clusters could be well separated in their privacy concerns (see table 13). Besides the two extreme groups, marginally concerned users (see table 13, cluster 1) and very concerned users (see table 13, cluster 4), two groups in between these extremes could be discerned. One group seemed to have a particular problem with the revelation of data such as postal address, e-mail address, phone number or credit card number (see table 13, cluster 2). The other group seemed to be more concerned about revealing information on computer equipment, salary, hobbies, health or age (see table 13, cluster 3). These two clusters were therefore called 'identity' and 'profile' concerned users. The distinction of the two groups-in-between was particularly pertinent for camera shoppers. Table 13 shows the details of these clusters with low (negative) values standing for low privacy concerns and high (positive) values standing for stronger privacy concerns.

Tabelle 13 Final Cluster Centres for K-means Cluster Analysis (Camera Shoppers):

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Z-Wert(INDEX 1)	-.6470	-.7472	.1850	.6132
Z-Wert(INDEX 3)	-.8163	.1962	.1735	.2007
Z-Wert(INDEX 4)	-.3343	-.2759	-.6846	.5269
Z-Wert(CONCERN ON	-.2124	-.3106	-.0101	.1517
Z-Wert(NAME)	-1.0424	-.5599	.3563	.4757
Z-Wert(ADDRESS)	-1.0488	-.6046	.4411	.4654
Z-Wert(EMAIL	-.8038	-.4687	.0674	.6202
Z-Wert(PHONE	-1.2049	-.1855	.2831	.4606
Z-Wert(COMPUTER)	-.7552	.0447	-.5905	.6549
Z-Wert(MONEYNEW)	-1.0210	.3327	-.5319	.6411
Z-Wert(CREDIT CARD	.1999	-.8702	.2439	.2549
Z-Wert(HOBBY AND	-.6917	-.0607	-.7215	.8267
Z-Wert(HEALTH)	-.8612	.5978	-.4953	.4536
Z-Wert(AGE)	-.7509	-.1307	-.5374	.7302

K-means analysis was then conducted on the basis of the entire sample, combining data from jacket and camera shoppers (see table C8, Appendix C). For this purpose, again, the target cluster number was set to four and cluster seeds were specified according to cluster centres derived from camera shoppers. The reason for choosing these cluster seeds was that it was wished to communicate the finding that there are, in fact, these distinct privacy preference, profile and identity concerns, which earlier studies could not discern [Ackerman et al., 1999]. Thus, it was possible to separate the "pragmatic majority" identified by Ackerman et al. [1999] into two more meaningful groups which were called "identity concerned" and "profiling averse" users. Figure 10 gives an overview over the four clusters identified and the share of users in these groups.

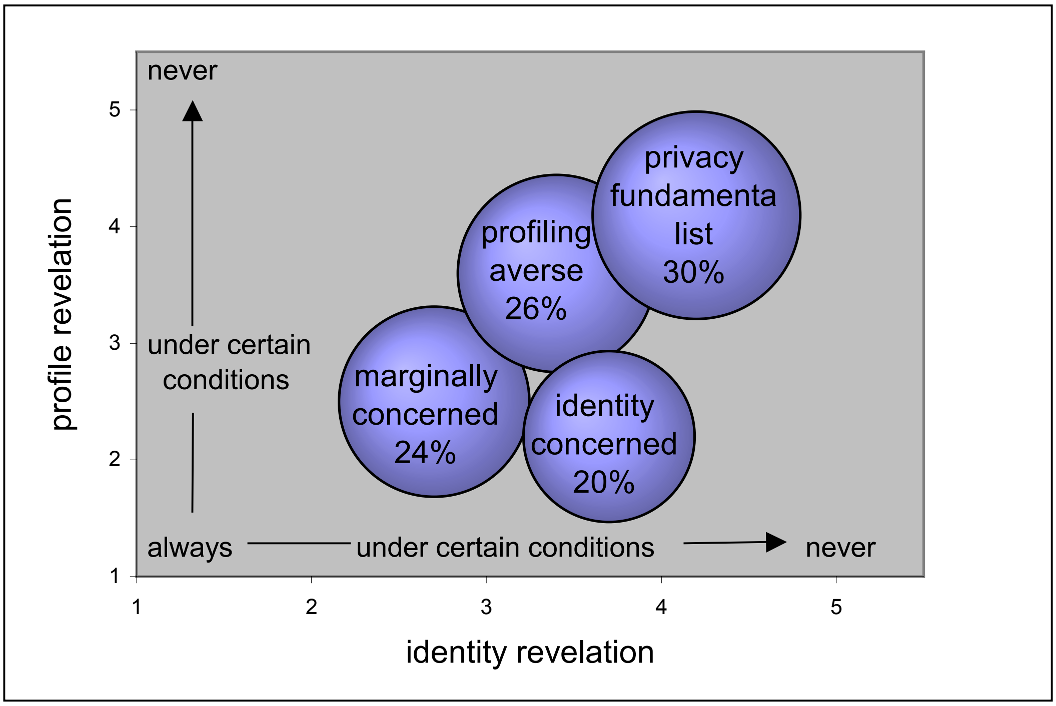


Abbildung 10: Four Clusters Reflecting Fear to Lose Privacy through Profile or Identity Revelation on the Internet

In sum, the privacy clusters suggest that among all participants there was a basic level of privacy concern. Against the background of older privacy studies cited above, this finding is not surprising. However, as has been discussed, the question still remains whether participants really act consistently with their expressed behavior.

For this purpose, it was investigated in a next step whether interaction behavior would be consistent with the attitudes stated. Two aspects of interaction behavior were considered: (a) whether participants voluntarily communicated their address to Luci before entering the question-answer cycle, and (b) how many and what types of questions participants answered when communicating with Luci. The first variable is a measure of the willingness to satisfy an information request separated from the sales dialogue and linked to identification. It was expected that 'identity concerned' users (cluster 3) would react particularly averse to this type of information provision. The second variable is a measure for the willingness to provide information embedded in a sales dialogue. Since many personal and profile-sensitive questions were asked in this communication context, it was expected that profiling averse users (cluster 2) would be particularly reserved.

6.3.3 Comparing Privacy Attitudes with Behavior

6.3.3.1 Address Provision

As described in chapter 3, all participants had to pass a html-page where agent Luci introduced herself and her purpose to the user and also gave participants the opportunity to leave their address (see screenshot ❹, Appendix B1b). No reason was specified why users should provide their address.

As expected from the nature of the cluster, marginally concerned users (cluster 1) had the lowest refusal rate in providing their home address for both privacy statements (30% for PS type 1 and 41% for PS type 2). Surprisingly, however, also 24-28% of privacy fundamentalists voluntarily provided their address before interacting with the agent. Identity concerned participants (cluster 3) also showed unexpected behavior. While under the condition of the 'softer' first privacy statement type 1 93% refused to provide their home address, only 65% did so under the even harsher conditions of privacy statement type 2. Thus, 35% of identity concerned users provided their home address without any reason to do so.[42] All observations are summarized in table 14.

Notably, across privacy statements there was an average of 35-40% of participants who gave their home address without any reason to do so. This raises the question how privacy conscious online users really are. In particular, the mentioning of the 'security providing' EU law in PS 1, led to an increase in voluntary address provision, as can be seen for most clusters in table 13. The average difference of 5% more address provision with EU law citation (11% without the inconsistent group of cluster 3) was interesting, though not significant (χ^2 (1) = 0.33, p > 0.5).

[42] The addresses provided were checked in the click-stream data and it seemed that no false addresses have been provided.

Tabelle 14: Contrasting Privacy Attitudes with Voluntary Address Provision

Privacy Clusters	PS type (voluntary address provision)	1PS type (no voluntary address provision)	1PS type (voluntary address provision)	2PS type (no voluntary address provision)	2 Sum of Participants
CL1:marginally concerned	14	6	13	9	42
% of cluster	70%	30%	59%	41%	
CL2: profiling averse	9	10	7	19	45
% of cluster	47%	53%	27%	73%	
CL3:identity concerned	1	13	7	13	34
% of cluster	7%	93%	35%	65%	
CL4: fundamentalists	7	18	6	19	50
% of cluster	28%	72%	24%	76%	
sum tot	31	47	33	60	171
% of sum	40%	60%	35%	65%	

6.3.3.2 Revelations During the Sales Dialogue

To represent the depth of interaction with the sales agent, the PCIC index described above was used. The PCIC index was calculated by inserting the number and type of questions answered by an individual participant into the PCIC regression functions A or B (table 12). The 171 PCIC index values where then split into terciles, contrasting individuals with low, medium and high disclosure. Table 15 summarizes the findings. Table 15 shows that participants from all clusters had a strong tendency to self-disclose. 87% of users were in the group with maximum PCIC values. This behavior could be observed across both product types, with 84% of camera shoppers and 98% of jacket shoppers in the highest PCIC group. Averaging across clusters, a mean of 85.8% of agent questions were answered (85.8% for cameras and 86.1% for jackets). As expected, however, the distribution of PCIC was different across clusters ($\chi^2(6)=16.57$, $p < .05$).

An investigation of cluster details showed that privacy fundamentalists (cluster 4) in particular did not live up to their expressed attitude. 78% of them display high PCIC values and answered an average of 86% of the agent questions. With this, they only answered 10 percentage points fewer questions than marginally concerned participants (cluster 1). Comparing behavior for the two product groups, it was found that for cameras only 83% of privacy fundamentalists had a high PCIC value, while for jackets 95% of fundamentalists were in this group. A difference of 7% in self-disclosure between the two products can also be observed for cluster 2. The findings hint at the possibility that the product category may have an influence on the extent of information revelation. This is consistent with the finding in section 4.3. that jacket shoppers had a tendency to answer and modify slightly more personal questions than camera shoppers.

Consistent with expectations, profiling averse participants (cluster 2) gave less information during the shopping dialogue than identity concerned participants (cluster 3). With 'only' 78% of people being in the high PCIC group. Therefore, clusters 2 and 4 turned out to be the groups with the most reserved behavior.

Mann-Whitney-U tests for different PCIC distributions across the two privacy statements generally ($p=0.969$) and for both products separately (camera: $p = .526$; jackets: $p = .227$) showed no significant differences in this obvious readiness of users to self-disclose. This is a surprising result as the privacy statement had been expected to have a greater impact on disclosure.

Tabelle 15: Contrasting Privacy Attitudes with Online Communication Behavior

Privacy Clusters	Low PCIC	Medium PCIC	High PCIC	Sum
CL1: marginally concerned	0	0	42	42
row %	0%	0%	100%	100%
total %	0%	0%	24%	24%
CL2: profiling averse	3	7	35	45
row %	7%	15%	78%	100%
total %	2%	4%	20%	26%
CL3: identity concerned	0	1	33	34
row %	0%	3%	97%	100%
total %	0%	1%	19%	20%
CL4: fundamentalists	3	8	39	50
row %	6%	16%	78%	100%
total %	2%	5%	23%	30%
Sum	6	16	149	171
total %	4%	9%	87%	100%

6.3.4 Discussion of Results

The results suggest that there is a huge discrepancy between online users' expressed privacy concern and their subsequent behavior. Regardless of their expressed attitudes towards the subject, the majority of participants were ready to reveal private and even highly personal information to the shopping agent and let themselves be 'drawn into' communication with the anthropomorphic agent. The degree of inconsistent behavior found in the data among 'privacy aware' clusters 2 to 4 are particularly surprising. The results are even more relevant when one considers the experimental conditions: after all, agent questions were designed to include many non-legitimate and unimportant personal questions. Participants also had to sign that they agreed to the selling of their data to an anonymous entity. As was mentioned in chapter 2, efforts had been made to minimize sympathy with the experimenters during the experimental briefing. The conditions under which participants 'revealed themselves' were therefore probably even less favourable in terms of privacy than a regular Internet shopping trip would be. At the same time, a very avant-garde technology was employed, using an interactive agent system that provided users with real recommendation benefits in return for their data. This benefit offered in return for user data is comparable to the business scheme of many companies such as bonus card issuers (e.g. Payback) that today offer customers discounts in return for their data [Chang et al., 1999]. On this background the findings indicate that even though Internet users have some view on privacy, they do not act accordingly when they expect a benefit from their revelations. This again is a fatal news to those who view privacy as a fundamental right. It suggests that the right to privacy or *"the right to be let alone"* [Warren and Brandeis, 1890] has become a tradable good which people are ready to sacrifice and commercialise.

6.4 Conclusion

Privacy concerns have been described as a major challenge for the design human – agent interaction. However, the results obtained on online users' privacy behavior in this study shed a new light on peoples privacy concern: while all users stated to be at least marginally concerned about privacy, few of them acted accordingly when it came to disclosing information to a 'sympathetic' agent. At the same time, it was observed that a significant tendency of experimental participants to reduce interaction time and page requests the more privacy concerns they expressed (see structural equation model results presented in chapter 3). Different strengths of privacy statements did not impact behavior.

Against the background of these findings it is hard to conclude whether privacy is finally an impeding factor for online consumers' interaction readiness with agents. Privacy surveys collecting consumers' attitudes as well as the findings from the equation model clearly indicate that people are concerned with their privacy. However, they seem to be willing to sacrifice it when responding to electronic shopping agents. There are two possible (and qualitative) explanations for this behavior, both of which probably deserve further research: First, participants may have consciously answered and modified agent questions, because they perceived the benefit from interaction, the product recommendation, to outweigh their cost of private information revelation. This assumes that online users make a cost-benefit evaluation when evaluating the worthiness of disclosure. At this point it is, however, interesting to note that 'rational' users should have realized that at least purely personal agent questions (peip-questions) could not possibly have been used by agent Luci to calculate a product recommendation (and thus providing the benefit). For example, answering the agent question "What do you usually do with your photographs?" (with answering options such as "collecting them in a box" or "glue them into an album") strictly cannot lead a shopping agent to calculate a better product recommendation. As a result, users should not have expected any benefit from answering this type of personal agent question. One debriefing interview with a student revealed that she (the student) had made an interesting junction between the respective agent question and the product recommendation. "Perhaps", she said, "the agent would respect in his recommendation that photos be put in an album and therefore expect the photos taken by the camera to be of really high quality". The student did not reflect on the fact that the development and quality of photographs (let alone album collection) are completely independent of the type of compact camera used. This type of illogic connection made in interacting with agents may be an interesting area of psychological research.

The second explanation why participants answered so many agent questions could simply be their ignorance when it comes to privacy implications of electronic communication. This potential ingenuousness was reflected in one debriefing interview with another participant who stated that (those conducting the experiment) would not be able to interpret his interaction behavior with sales agent Luci for, after all, he (the participant) had 'erased' all initial answers provided to the agent once he had profited from recommendations. Thus, obviously, the participant was not aware of the fact that every user request is logged by the server providing the web site service and that for this reason all his preference data (as well as the erasure process of course) had been registered. The anecdote goes in line with Goldberg stating in 1997 [Goldberg, 1997]: *"New users of the Internet generally do not realize that every post they make to a newsgroup, every piece of e-mail they send, every World Wide Web page they access, and every item they purchase online could be monitored or logged by some unseen third party."* For the current analysis, it must however be mentioned again that 86,7% of the participants had stated to regularly use Internet and e-mail which puts our findings in another light: they suggest that even frequent users are not necessarily knowledgeable about the technological processes taking place 'behind the screen' and are thus not capable to effectively protect their privacy.

Chapter 7

7 Thesis Conclusions and Impulses for Future Research

This thesis has investigated how consumers search for high-involvement product information online. The conclusions of this investigation are based on a significantly rich data set, generated by a large-scale, real-world experiment. Over 270 subjects were observed in their online behavior and their dealings with an electronic agent while shopping for winter jackets and compact cameras.

A number of valuable insights have been gained regarding what drives consumers to interact with agents, and what impedes them, in their search for online product information during high-involvement purchase interactions.

One major finding is that agents do not play the same role in, and are not equally important for, online information search in different product categories. This has become clear from a theoretical perspective, regarding agent roles in different purchase tasks, as well as upon the empirical investigations made. Communication with agent Luci was comparatively less important for jacket shoppers than it was for camera shoppers, because jacket shoppers displayed a high need for product visualization and wished to have an overview of the available product spectrum.

The search for cameras, in contrast, was more 'fact-driven' and, as a result, the relative importance of the agent was higher. As cameras and jackets were perceived as search and experience goods, respectively, by experimental participants, it would be interesting to investigate to what extend this product classification cannot be used to explain consumer–agent interaction more systematically. To what extend are electronic agents capable to at all transmit experience qualities of goods? More insights into how product classes call for or impede agent use would certainly be invaluable for the online retail industry, especially during investment deliberations regarding front-end technology.

A major aspect of this thesis was the separation of online information search into two constructs, manually controlled and agent-assisted search. This separation allowed to observe that, at a significant level, consumers prefer to manually control the search process the more risk they perceive. Consequently, electronic advisor agents are relatively less relied upon in the information search process. A similar direction of behavior was found for product knowledge. In line with older studies [Urban et al., 1999] our model suggests that the more product knowledge a consumer perceives the less he interacts with an agent for information search purposes. However, this result must be regarded with caution as the system employed in the current experiment did not offer a high-level expert-exchange for more knowledgeable customers.

Finally, a potentially major impediment for agent interaction has been investigated in detail: privacy concerns. The results obtained are interesting in that, against expectations, privacy concerns to not impede disclosure. In contrast, if systems offer appropriate returns in the form of personalized recommendations online users seem to be ready to reveal even highly personal information. And there is no incentive for them to lie as this behavior would adversely affect the benefit of search (the recommendation quality). The finding suggests that there is a lot of room for online marketers to communicate with their clients through dialogue-based electronic agents. If marketers used the spectrum of legitimate personal questions that are related to the product selection process more systematically, they could gain valuable insight into their customers' decision making process as well as on decisive product attributes. However, unfavorable privacy settings do seem to induce a feeling of discomfort among some users which then leads to less interaction time. Marketers therefore have to provide for a comforting privacy environment in order to make their customers feel good about the interaction.

Summing up, evidence has been generated in this thesis that users have a strong desire to control the information search process. The only significant driver of agent assisted search that could be supported by the structural equation model was purchase involvement. Thus, the more people had an immediate need for the product, the more they performed a search using the agent. However, this behavior was true in the same way for manual search. Thus, the vision of 'agents that buy and sell' for consumers [Maes et al., 1999] or that take over the entire purchase process for consumers without recurring back to them [Borking et al., 1999; Pazgal, 1999] must clearly be questioned against the background of this thesis' findings. At the same time, the often cited challenge of agents to overcome privacy concerns appears to be of rather marginal importance as consumers enjoy 'talking about themselves' online and benefit from personalized recommendations. These findings, which are in many respects surprising, suggest that it is easy to have misconceptions about how consumers deal with electronic advisor agents. And, given this, a whole new field of research opens up: management, reliance and trust upon relationships between humans and artificial entities.

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A – HANDOUT MATERIAL & BRIEFINGS

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7. Eiinsammeln des Fragebogens 1
8. Einführung in das Experiment; Text: Ziel der Stuiden: „Wir haben für einen großen europäischen Internetanbieter eine Suchmaschine entwickelt, die wir mit Ihrer Hilfe testen möchten.“; „Hauptziel des Experiments ist es, Ihr Interaktionsverhalten, also Ihren Umgang mit der Suchmaschine zu untersuchen, während Sie online ‚stöbern’ und versuchen, das für Sie richtige Produkt zu identifizieren.“; „Verhalten Sie sich deshalb so „natürlich“ wie möglich; also so, wie Sie sich verhalten würden, wären Sie jetzt zu Hause an Ihrem eigenen PC. Dies ist auch wichtig, damit wir Ihnen ein für Sie aussagekräftiges Feedback auf Ihr Interaktionsverhalten geben können.“; „Wenn Sie also mit dem Shoppen fertig sind, dann hören Sie also bitte einfach auf und verweilen Sie nicht mehr im Shop.“„Sie erhalten dieses Feedback per Mail von uns automatisch im nächsten Frühjahr zugeschickt.“Anmerkung zum Ablauf: „Das Experiment bedingt, dass alle Teilnehmer so lange an Ihren Plätzen sitzen bleiben müssen, bis auch alle anderen mit dem Shoppen fertig sind. Daher: es bringt nichts, durch die Shopping Session zu ‚rasen’. “„Allerdings können alle fertigen Teilnehmer, wie eben vereinbart, doch spätestens um 5 Min vor X Uhr den Raum verlassen. Wir bitten hier insgesamt um Ihr Verständnis.“
9. Austeilen der Interface Erklärungen
10. Vorlesen der Interface Erklärungen

11. Austeilen des Privacy Statement zur Unterschrift; Anmerkungen zu Privacy Statement: „Sie müssen verstehen, dass es sich hier um ein ‚echtes Online-Experiment' handelt. Das heißt, dass alle persönlichen Informationen, die Sie uns im Rahmen Ihrer Shopping Session mitteilen, nicht bei uns liegen, sondern in die Datenbank des industriellen Sponsors eingehen. Wir wissen nicht, was der Sponsor mit Ihren Angaben macht, ob er sie nur für Analysezwecke nutzt oder verkauft.Ihr 60% Discount wird über diese Datenweitergabe finanziert. Wie die meisten von Ihnen wissen, ist es bei Käufen auf dem WWW immer so, dass Ihre Angaben registriert werden. Alles was Sie auf dem Netz tun, kann von dem jeweiligen Vermarkter genutzt werden. Es werden i.d.R. Profile von Ihnen erstellt, die Ihr Verhalten, Ihre Bedürfnisse und Präferenzen abbilden. Wir möchten Sie bitten, Ihr Einverständnis zu Ihrer Datenweitergabe schriftlich zu geben."; „Wir möchten jedoch darauf hinweisen, dass alle Angaben, die Sie uns vor und nach dem Onlinekauf auf Papier gemacht haben und machen werden nicht weitergegeben werden, sondern nur von uns und absolut vertraulich behandelt werden."
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A2. Consent of Payment

Zahlungserklärung

Hiermit verpflichte ich mich, 40% des im Online-Shop* aufgeführten ‚Ladenpreises' in bar zu entrichten**, sollte ich im Rahmen des Experiments das Produkt gekauft haben ***und*** sollte ferner das Los (mit einer Chance von 1:10) auf mich gefallen sein. Im Gegenzug dazu erhalte ich das Produkt meiner Wahl sowie den Kassenbon.

*Der Online-Shop ist das Verkaufsinterface, welches im Rahmen des ‚Weihnachtsexperiments' der Institute Wirtschaftstheorie III und Wirtschaftsinformatik entwickelt worden ist.

**Die Zahlung werde ich bei Entgegennahme der Winterjacke oder der Kompaktkamera im Sekretariat für Wirtschaftstheorie III noch vor Weihnachten entrichten

____

Name in Druckschrift

____

Berlin, den

____

Unterschrift

A3. Privacy Statements

A3a) PS type 1 (soft)

Information zum Umgang mit Ihren privaten Daten

Wir möchten Sie darauf hinweisen, daß die im Rahmen dieses Experiments von Ihnen gesammelten Daten an den industriellen Sponsor des Projekts ***zu Analysezwecken*** weitergereicht werden. Der Sponsor ist ein seriöses, europäisches Großunternehmen. Er unterliegt gesetzlich der EU Gesetzgebung zum Umgang mit persönlichen Daten.

Die EU Direktive 95/46/EC zum Schutz persönlicher Daten vom 25. Oktober 1998 beinhaltet vor allem die folgenden Rechte:

- Das Recht von späteren Nutzern der Daten zu erfahren, wo die Informationen herkommen, welche Organisation die Daten weiter verarbeitet und zu welchem Zweck dies geschieht.
- Das Recht die persönlichen Daten einzusehen.
- Das Recht persönliche Daten zu verändern sofern diese als falsch nachgewiesen werden können.
- Das Recht unter bestimmten Umständen (wie z.B. Direktmarketingaktivitäten) die weitere Nutzung der persönlichen Daten zu unterbinden.

Einverständniserklärung zum Umgang mit privaten Daten

Hiermit erkläre ich mich damit einverstanden, daß die im Rahmen dieses Experiments von mir gesammelten Daten an den industriellen Sponsor des Projekts zu Analysezwecken weitergereicht werden.

____

Ort, Datum

____

Unterschrift

A3b) PS type 2 (harsh)

Information zum Umgang mit Ihren privaten Daten

Wir möchten Sie darauf hinweisen, daß die im Rahmen dieses Experiments von Ihnen gesammelten Daten an den industriellen Sponsor des Projekts weitergereicht werden. Wir wissen nicht, was der Sponsor mit diesen Informationen macht. Der Sponsor ist ein seriöses, europäisches Großunternehmen.

Wenn Sie im Rahmen des Experiments kaufen, sind Sie verpflichtet, Ihre Adresse anzugeben.

Einverständniserklärung zum Umgang mit privaten Daten

Hiermit erkläre ich mich damit einverstanden, daß die im Rahmen dieses Experiments von mir gesammelten Daten an den industriellen Sponsor des Projekts weitergereicht werden.

____

Ort, Datum

____

Unterschrift

A.4. Description of Navigation Opportunities in the Store

A4 – DESCRIPTION OF NAVIGATION OPPORTUNITIES IN THE STORE

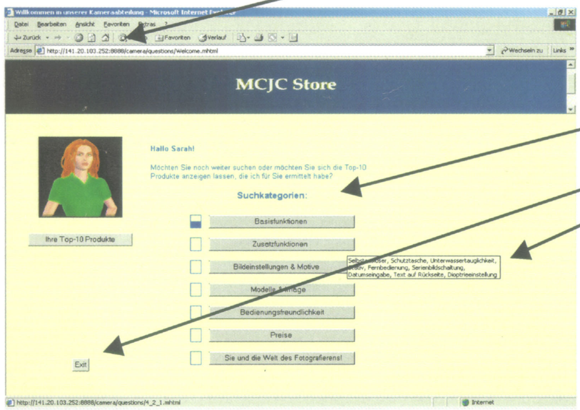
Erklärungen zum Umgang mit dem Shop

Allgemein: Bitte vermeiden Sie Nutzung der Explorer Task-Leiste und benutzen Sie nur die Befehlbuttons direkt auf der Seite!

Eingangsseiten des Shops

Explorer Task-Leiste

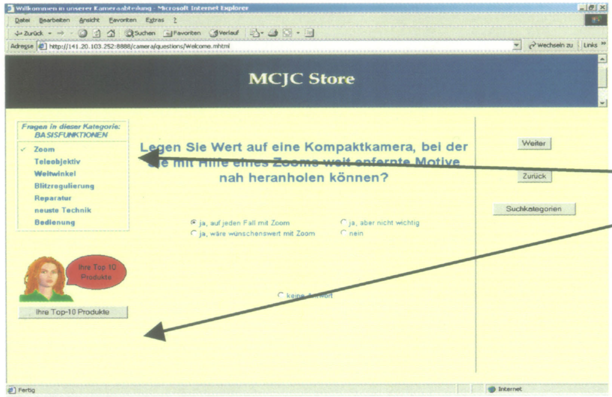
HOME der Suchmaschine LUCI:



Sehen Sie sich in Ruhe alle Suchkategorien an!

- Luci funktioniert besser, wenn aus **unterschiedlichen** Suchkategorien Fragen beantwortet werden
- Mit dem „Exit"-Button können Sie jederzeit die Shopping Tour beenden
- Wenn Sie die Maus auf eine Suchkategorie halten, erscheint deren Inhalt

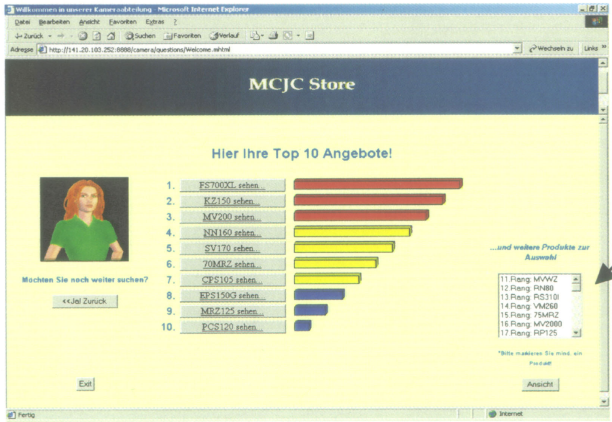
Fragen der Suchmaschine LUCI:



Wir lassen Ihnen grundsätzlich immer die Möglichkeit, keine Angaben zu machen!

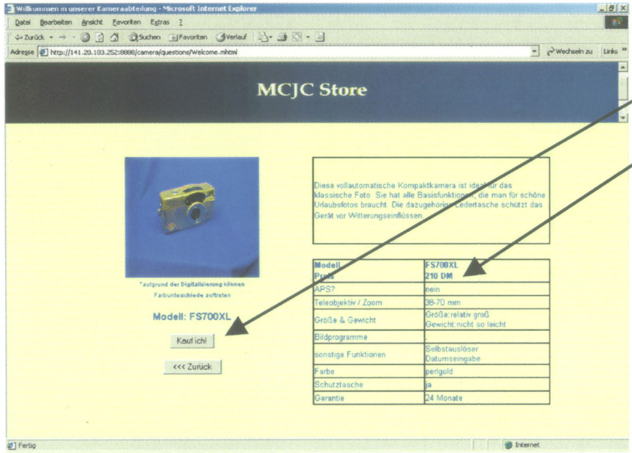
- Wir würden Sie daher bitten, dass **wenn Sie sich entschließen, Angaben zu machen, dann bitte wahrheitsgemäß**. Lieber nichts sagen als lügen, da sonst unsere Ergebnisse total verfälscht sind.
- Die Übersicht zeigt, welche Fragen noch kommen
- Wenn gar keine Fragen beantwortet werden, sind die Top-10 Produkte ein Zufallsprodukt

LUCIs ermittelte Top-10 Produkte:



- Die Top-10 Produkte werden auf Basis eines von uns entwickelten Algorithmus ermittelt. Wir haben diesen Algorithmus bereits mehrmals mit großem Erfolg getestet.
- Weitere Produkte sind in abnehmender Attraktivität für Sie geordnet.

Der Produktsteckbrief:



- Wenn Sie kaufen, verpflichten Sie sich 40% des Ladenpreises an uns in den nächsten Tagen auszuzahlen
- Der hier angegebene Ladenpreis ist der Ursprungspreis des Produkts, auf den Sie im Falle eines Kaufes 60% Discount erhalten würden.
- Jeder hat nur Anrecht auf 1 Produkt.

Bitte melden Sie sich, wenn Sie mit dem Shoppingtrip fertig sind! Wir möchten Ihnen dann noch ein paar abschließende Fragen stellen.

A.5. Pre & Post Shopping Questionnaires

The questionnaire version integrated in this appendix is the one handed to camera shoppers. Questions for camera and jacket shoppers were identical with the one exception that sometimes the wording had to be adapted to the camera or jacket context (e.g. "You are going to buy in a moment a camera/jacket….").

The questionnaire presented here also contains the literature from where many questions were derived as well the content structure that has served as a basis for development. Experimental participants did not see the literature sources or content structure listed here as an additional information.

A 5A – PRE SHOPPING QUESTIONNAIRE

Fragebogen 1

Kamerakauf

Bevor Sie in unserem Online-Store eine Kamera kaufen, bitten wir Sie noch eine Reihe von Fragen zu beantworten. Ihre Antworten sind für uns wichtig, um Ihr Kaufverhalten hinterher richtig interpretieren zu können. Bitte beachten Sie beim Ausfüllen des Fragebogens, daß es keine „richtigen" oder „falschen" Antworten gibt. Verweilen Sie auch nicht zu lange bei einer Aussage. Teilweise mögen Ihnen die Fragen recht ähnlich erscheinen. Dies ist Absicht! Bitte versuchen Sie, so aufrichtig wie möglich zu antworten! Ihre Antworten werden absolut vertraulich behandelt.

Ihre ID?

Wie alt sind Sie? ________________________________

Welches Geschlecht haben Sie?

❑ männlich
❑ weiblich

Welche Nationalität haben Sie?______________________________________

Wenn Sie deutsch sind: Kommen Sie ursprünglich aus West- oder Ostdeutschland?

❑ Ost
❑ West

Wenn Sie noch studieren: welches Fach? ______________________________________

Wenn nicht, welchen Beruf üben Sie aus? ______________________________________

Umgang mit dem Internet (Ackerman, 1999)

Haben Sie einen eigenen Computer (Laptop oder PC) oder zumindest einen, auf den Sie regelmäßig zugreifen können?

❑ ja
❑ nein

Senden und empfangen Sie e-mails?

❑ ja, regelmäßig	❑ sehr selten
❑ ja, manchmal	❑ nie

Benutzen Sie das Internet (vor allem WWW)?

❑ ja, regelmäßig	❑ sehr selten
❑ ja, manchmal	❑ nie

8. Wann waren Sie das letzte Mal online (e-mail oder Internet)?

❑ vor 24 Stunden
❑ vor 48 Stunden
❑ vor 1 Woche
❑ vor 2 Wochen
❑ innerhalb des letzten Monats
❑ innerhalb der letzten 2 Monate
❑ länger her

9. Wie oft haben Sie in den letzten 12 Monaten einen Onlinekauf getätigt?
❑ gar nicht
❑ 1mal
❑ 2 mal
❑ 3 mal
❑ > 3 mal

Welche Erfahrung haben Sie mit Onlinekäufen gemacht?

❑ nur gute
❑ überwiegend gute
❑ überwiegend schlechte
❑ nur schlechte
❑ keine

Produktwissen, vorhandene Produkterfahrung, Produktinteresse

Produktwissen und –interesse

Wie stark trifft auf Sie die folgende Aussage zu?

Im Vergleich zum Durchschnittsbürger weiß ich schon eine Menge über elektronische Geräte (z.B. Hifi-Anlagen, Kameras, Fernseher, Computer etc.)! ***(Srinivasan und Ratchford, 1991)***

- ❑ trifft voll zu
- ❑ trifft eher zu
- ❑ trifft teils teils zu
- ❑ trifft eher nicht zu
- ❑ trifft überhaupt nicht zu

Wie häufig lesen Sie über elektronische Geräte (z.B. deren Neuheiten) in Zeitschriften? *(Kiel und Layton, 1981)*

- ❑ regelmäßig (min. 2 Mal im Monat)
- ❑ häufig (min. 1 Mal im Monat)
- ❑ manchmal (alle paar Monate mal)
- ❑ selten (ca. 1 Mal im Jahr)
- ❑ nie

Wie häufig unterhalten Sie sich mit Freunden, Familie oder Bekannten über elektronische Geräte? *(Kiel und Layton, 1981; Srinivason und Ratchford, 1991)*

- ❑ regelmäßig (min. 2 Mal im Monat)
- ❑ häufig (min. 1 Mal im Monat)
- ❑ manchmal (alle paar Monate mal)
- ❑ selten (ca. 1 Mal im Jahr)
- ❑ nie

Produkterfahrung

Wie viele größere Anschaffungen (>200,-DM je Produkt) haben Sie im Bereich elektronischer Geräte in den letzten 24 Monaten gemacht? *(Kiel und Layton, 1981; Punj and Staelin, 1983)*

❑ keine
❑ 1
❑ 2
❑ 3
❑ > 3

Wie lange ist es her, daß Sie sich das letzte Mal eine Kamera gekauft haben? *(Punj and Staelin, 1983)*

❑ < 1 Monat
❑ 1-3 Monate
❑ 3-6 Monate
❑ 6-12 Monate
❑ > 12 Monate
❑ habe noch nie eine Kamera gekauft

Wie stark trifft auf Sie die folgende Aussage zu?

Ich berate andere Leute regelmäßig bei der Wahl elektronischer Geräte! *(Moore and Lehmann, 1980)*

❑ trifft voll zu
❑ trifft eher zu
❑ trifft teils teils zu
❑ trifft eher nicht zu
❑ trifft überhaupt nicht zu

Haben Sie sich bevor Sie hier zu uns ins Labor gekommen sind noch einmal zu dem Produkt informiert, für welches Sie sich angemeldet haben (sind z.B. in ein Geschäft gegangen, um sich verschiedene Modelle anzuschauen)?

❑ ja
❑ nein

Haben Sie beim Kauf einer Kamera oder eines anderen elektronischen Gerätes schon einmal eine schlechte Erfahrung gemacht; z.B. dahingehend, daß das Gerät schneller kaputt gegangen ist als erwartet oder aber bestimmte Funktionen nicht hatte, die Sie wollten?

❑ ja
❑ nein

Budget

Angenommen Sie kaufen eine Kamera und kurz nach dem Erwerb wird Ihnen diese gestohlen. Was machen Sie? *(Dowling and Staelin, 1994)*

❑ ich würde mir die gleiche Kamera noch einmal neu kaufen
❑ ich würde mir wahrscheinlich eine billigere Kamera als Ersatz kaufen
❑ ich würde die Kamera zunächst nicht ersetzen

Wie stark stimmen Sie der folgenden Aussage zu?

Was Kameras betrifft, habe ich ein stark begrenztes Budget! *(Moore and Lehmann, 1980)*

❑ trifft voll zu
❑ trifft eher zu
❑ trifft teils teils zu
❑ trifft eher nicht zu
❑ trifft überhaupt nicht zu

Selbstsicherheit

Wie wichtig ist Ihnen beim Kauf einer Kamera grds. die Meinung ihrer Freunde, Bekannten oder Familie? *(Kiel und Layton, 1981)*

❑ sehr wichtig
❑ wichtig
❑ unterschiedlich
❑ weniger wichtig
❑ überhaupt nicht wichtig

Einstellungen zur Privatheit im Internet (Ackerman et al., 1999)

Wie stark tangiert Sie eine potentielle Einbuße an Privatsphäre durch die Nutzung des Internets?

❑ sehr stark
❑ stark
❑ tangiert mich eher weniger
❑ tangiert mich überhaupt nicht

Szenario 1: Stellen Sie sich vor, Sie gingen auf die WWW-Seite Ihrer Hausbank und entdeckten ein elektronisches Formular, welches Sie ausfüllen können, um daraufhin auf Sie persönlich zugeschnittene Anlageempfehlungen zu bekommen. Auf dem Formular werden Sie gebeten, Angaben zu Ihrem Einkommen, Ihren gegenwärtigen Anlagen und Sparzielen zu machen. Gleichzeitig werden keine Angaben zu Ihrer Person, Ihrem Namen oder andere Informationen abgefragt, von denen auf Ihre Person geschlossen werden könnte. Ausgehend von den Informationen auf der Website sieht es so aus, als könnten Sie durch das Ausfüllen des Formulars nützliche Informationen bekommen.

Würden Sie das Formular ausfüllen?

❑ Auf gar keinen Fall
❑ Wahrscheinlich nicht
❑ Ich bin nicht sicher
❑ Wahrscheinlich schon
❑ Ganz bestimmt

Wie würden Sie sich in ***Szenario 1*** verhalten, angenommen das Formular würde doch nach Ihrem Namen und Ihrer Adresse fragen, so dass Ihnen die Bank einen Anlageführer zuschicken kann? Nehmen Sie an, dass dieser Anlageführer für Sie nützlich sein könnte.

Würden Sie die Angaben (Namen und Adresse) machen?

❑ Auf gar keinen Fall
❑ Wahrscheinlich nicht
❑ Ich bin nicht sicher
❑ Wahrscheinlich schon
❑ Ganz bestimmt

Szenario 2: Bei einem anderen Onlinebesuch bei der Website Ihrer Hausbank erfahren Sie von einem neuen Bankservice, für den Sie sich online registrieren lassen können. Einer Ihrer Freunde hat Ihnen von diesem Service schon erzählt und davon, wie leicht es ist, sich dafür anzumelden. Sie entscheiden, daß dieser Service auch für Sie nützlich sein kann und gehen deshalb auf den Link, um sich zu registrieren. Das Registrierformular fragt Sie nach Ihrem Namen und Ihrer Kontonummer. Ihre Angaben werden verschlüsselt übertragen, so daß niemand Ihre Angaben lesen kann bis sie bei der Bank eintreffen. Wie würden Sie voraussichtlich in diesem Szenario reagieren?

❑ Ich würde die verlangte Information eingeben
❑ Ich würde meine Bank entweder anrufen oder mich dort persönlich für den neuen Service anmelden
❑ Ich würde mich für den neuen Service nicht anmelden

Szenario 3: Während Sie online Informationen zu einem Ihrer Lieblingshobbies suchen, landen Sie auf einer Website, die ein paar wirklich interessante Informationen enthält. Die Site wird gesponsert von einer Firma, deren Name Sie noch nie gehört haben, aber die Leute scheinen sich auszukennen. Sie finden ein Formular auf der Seite, welches Sie ausfüllen können, um eine kostenlose Broschüre und einige Zusatzinformationen zu erhalten sowie Gutscheine auf einige Produkte der Firma. Das Formular verlangt Ihren Namen und Ihre Postanschrift. Wie würden Sie voraussichtlich reagieren?

❑ Ich würde die verlangte Information eingeben
❑ Ich würde versuchen, die Firma anzurufen, um so die Broschüre und die Gutscheine zu bekommen
❑ Ich würde wahrscheinlich auf die Möglichkeit verzichten, die Broschüre und die Gutscheine zu bekommen

Wie würden Sie Ihr Verhalten in ***Szenario 3*** (Frage 26) ändern, enthielte die Website eine Erklärung zum Umgang mit Ihren Daten (privacy policy). In der Police steht, daß die Firma Ihren Namen und Ihre Adresse ausschließlich nutzen wird, um Ihnen die angeforderte Broschüre und die Gutscheine zuzuschicken.

❑ An meiner Reaktion würde sich nichts ändern
❑ Ich würde die verlangte Information eher eingeben
❑ Ich würde weniger gewillt sein, die verlangte Information einzugeben

Wie würde sich Ihr Verhalten in ***Szenario 3*** (Frage 26) ändern, enthielte die Website nicht nur eine Privacy Police, sondern außerdem noch das Gütesiegel einer anerkannten Organisation, wie z.B. dem TÜV, die für die Vertrauenswürdigkeit der Website garantiert?

❑ An meiner Reaktion würde sich nichts ändern
❑ Ich würde die verlangte Information eher eingeben
❑ Ich würde weniger gewillt sein, die verlangte Information einzugeben

Wie würden Sie Ihr Verhalten in ***Szenario 3*** (Frage 26) ändern, gäbe es ein Gesetz, welches dem Betreiber der WWW Seite verbietet, Ihren Namen und Ihre Adresse für einen anderen Zweck als Ihre Anfrage einzusetzen.

❑ An meiner Reaktion würde sich nichts ändern
❑ Ich würde die verlangte Information eher eingeben
❑ Ich würde weniger gewillt sein, die verlangte Information einzugeben

Wie würde sich Ihr Verhalten in ***Szenario 3*** (Frage 26) ändern, enthielte die Website eine Privacy Police, die Ihnen erklärt, daß die Firma Ihren Namen und Ihre Adresse nicht nur dafür nutzen möchte, Ihnen die angeforderte Broschüre und die Gutscheine zuzuschicken, sondern auch, um Ihnen in Zukunft regelmäßig Neuigkeiten zu ihren Produkten zukommen zu lassen. Ferner plant die Firma Ihre Daten auch anderen Unternehmen zur Verfügung zu stellen, die Produkte verkaufen, für die Sie sich eventuell auch interessieren könnten.

❑ An meiner Reaktion würde sich nichts ändern
❑ Ich würde die verlangte Information eher eingeben
❑ Ich würde weniger gewillt sein, die verlangte Information einzugeben

Wären Sie in Frage 30 eher bereit die Information einzugeben, wenn die Website Ihnen die Möglichkeit geben würde, auf Wunsch von ihrer Mailingliste jederzeit wieder entfernt zu werden?

❑ ja
❑ nein

Szenario 4: Sie besuchen eine Website, die Nachrichten, Wetter und Sportergebnisse bereitstellt. Sie finden die Seite sehr ansprechend und würden Sie in Zukunft gerne häufiger besuchen. Die Website fordert Sie auf, Ihre Postleitzahl anzugeben sowie einige Fragen zu Ihren Interessen zu beantworten, damit die Interaktion mit der Website in Zukunft auf Sie persönlich zugeschnitten werden kann. Die Privacy Police der Website erklärt, daß alle Informationen, die Sie angeben sowie Ihr Suchverhalten auf der Website registriert werden. Beides wird genutzt, um die Seiten auf Sie ‚zuzuschneiden' und um die Seite insgesamt zu erhalten und zu verbessern. Gewährleistet ist, daß Ihr Name nie mit diesen Informationen assoziiert wird. Wie würden Sie voraussichtlich reagieren?

❑ Ich würde die verlangte Information eingeben
❑ Ich würde die verlangte Information nicht eingeben
❑ Ich würde die verlangte Information vielleicht eingeben, aber wahrscheinlich würde ich lügen

Wie würden Sie in ***Szenario 4*** (Frage 32) reagieren, wenn die Website Sie außerdem nach einigen Informationen über Ihren Computer fragt, damit die Seite besser auf Sie zugeschnitten werden kann. Die Fragen könnten Informationen zu dem von Ihnen genutzten Betriebssystem, dem Browser, dem Monitor oder Modem enthalten.

❑ An meiner Reaktion würde sich nichts ändern
❑ Ich würde die verlangte Information eher eingeben
❑ Ich würde weniger gewillt sein, die verlangte Information einzugeben
❑ Ich würde die verlangte Information vielleicht eingeben, aber wahrscheinlich würde ich lügen

Wie würden Sie in ***Szenario 4*** (Frage 32) reagieren, wenn die Website von Ihnen demographische oder soziographische Informationen abfragt, eingeschlossen Ihr Alter, Ihr Geschlecht und Ihr Familieneinkommen?

❑ An meiner Reaktion würde sich nichts ändern
❑ Ich würde die verlangte Information eher eingeben
❑ Ich würde weniger gewillt sein, die verlangte Information einzugeben
❑ Ich würde die verlangte Information vielleicht eingeben, aber wahrscheinlich würde ich lügen

Wie würden Sie in ***Szenario 4*** (Frage 32) reagieren, wenn die Website Ihren Namen abfragt?

❑ An meiner Reaktion würde sich nichts ändern
❑ Ich würde die verlangte Information eher eingeben
❑ Ich würde weniger gewillt sein, die verlangte Information einzugeben
❑ Ich würde die verlangte Information vielleicht eingeben, aber wahrscheinlich würde ich lügen

Wie würden Sie in ***Szenario 4*** (Frage 32) reagieren, wenn die Website Ihren Namen wissen möchte, ihre Privacy Police jedoch aussagt, daß wenn Sie die Website über 3 Monate nicht besuchen, Ihr Name und alle Informationen gelöscht werden, die man über Sie gesammelt hat.

❑ An meiner Reaktion würde sich nichts ändern
❑ Ich würde die verlangte Information eher eingeben
❑ Ich würde weniger gewillt sein, die verlangte Information einzugeben
❑ Ich würde die verlangte Information vielleicht eingeben, aber wahrscheinlich würde ich lügen

Für wie zuverlässig und vertrauenswürdig halten Sie grundsätzlich Erklärungen von Internetanbietern zum Umgang mit Ihren persönlichen Daten?

❑ Ich halte sie für sehr vertrauenswürdig
❑ Ich halte sie für eher vertrauenswürdig
❑ Ich halte sie für teils teils vertrauenswürdig
❑ Ich halte sie für eher nicht vertrauenswürdig
❑ Ich halte sie für überhaupt nicht vertrauenswürdig

Beim Besuch von Websites, die Informationen über User sammeln, besteht bei vielen Leuten die Haltung, daß sie einige Informationen grundsätzlich bedenkenlos herausgeben, während sie andere Informationen nur unter besonderen Umständen von sich preisgeben. Wieder andere Informationen würden sie nur sehr ungern oder nie auf einer Website hinterlassen. Bitte sagen Sie uns, wie wohl Sie sich dabei fühlen, die folgenden Informationen auf einer Website anzugeben.

Ihren Vor- und Nachnamen

❑ Ich würde mich *immer* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *normalerweise* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *unter bestimmten Umständen* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *selten* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *nie* wohl fühlen, diese Information auf einer Website anzugeben.

Ihre Postanschrift

❑ Ich würde mich *immer* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *normalerweise* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *unter bestimmten Umständen* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *selten* wohl fühlen, diese Information auf einer Website anzugeben.

❑ Ich würde mich *nie* wohl fühlen, diese Information auf einer Website anzugeben.

Ihre e-mail Adresse

❑ Ich würde mich *immer* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *normalerweise* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *unter bestimmten Umständen* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *selten* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *nie* wohl fühlen, diese Information auf einer Website anzugeben.

Ihre Telefonnummer

❑ Ich würde mich *immer* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *normalerweise* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *unter bestimmten Umständen* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *selten* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *nie* wohl fühlen, diese Information auf einer Website anzugeben.

Informationen über Ihren Computer, Hardware und Software

❑ Ich würde mich *immer* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *normalerweise* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *unter bestimmten Umständen* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *selten* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *nie* wohl fühlen, diese Information auf einer Website anzugeben.

Ihr jährliches Haushaltseinkommen

❑ Ich würde mich *immer* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *normalerweise* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *unter bestimmten Umständen* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *selten* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *nie* wohl fühlen, diese Information auf einer Website anzugeben.

Ihre Kreditkartennummer

❑ Ich würde mich *immer* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *normalerweise* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *unter bestimmten Umständen* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *selten* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *nie* wohl fühlen, diese Information auf einer Website anzugeben.

Informationen über Ihre Hobbies

❑ Ich würde mich *immer* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *normalerweise* wohl fühlen, diese Information auf einer Website anzugeben.

❑ Ich würde mich *unter bestimmten Umständen* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *selten* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *nie* wohl fühlen, diese Information auf einer Website anzugeben.

Informationen über Ihre Gesundheit und Krankheitsgeschichte

❑ Ich würde mich *immer* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *normalerweise* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *unter bestimmten Umständen* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *selten* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *nie* wohl fühlen, diese Information auf einer Website anzugeben.

Ihr Alter

❑ Ich würde mich *immer* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *normalerweise* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *unter bestimmten Umständen* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *selten* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *nie* wohl fühlen, diese Information auf einer Website anzugeben.

Fragen zu Kaufzielen & Involvement

Möchten Sie die Kamera für sich selbst kaufen oder als Geschenk für jemand anderen?

❑ für mich selbst
❑ als Geschenk
❑ weder noch

Wie wichtig ist es Ihnen, in **unserem** Onlinestore **heute** eine Ihren Vorstellungen entsprechende Kamera zu einem Discount von **60%** wirklich zu finden?

❑ sehr wichtig
❑ eher wichtig
❑ unentschlossen
❑ eher weniger wichtig
❑ überhaupt nicht wichtig

Wie dringend wünschen Sie sich eine Kamera?

❑ sehr dringend
❑ dringend
❑ nicht so dringend
❑ überhaupt nicht dringend

Fragen zur Wahrnehmung von Produkten:

Wahrgenommenes Produktrisiko (Cunningham, 1967; Kroeber-Riel, 1994, Bettman 1973, 1975)

Stellen Sie sich vor, Sie sollten in der nächsten Stunde hier, online, nicht nur eine Kompaktkamera für 200,- bis 600,- DM auf eigene Rechnung über unseren WWW-Store kaufen, sondern außerdem noch einen Gebrauchtwagen (für ca. 10.000-12.000,- DM), eine Tube Zahncreme (für ca. 3-8,- DM) und eine Winterjacke (für ca. 200-600,- DM). Keines dieser Produkte können Sie sich physisch anschauen vor dem Kauf; jedoch gibt es ein Foto von jedem Modell. Stellen Sie sich bitte auch vor, dass **die Produkte keine Marken erkennen lassen**! Bitte beantworten Sie vor diesem Hintergrund folgende Fragen, indem Sie ein ‚❍' ankreuzen oder füllen:

Wie wahrscheinlich ist es, daß sich der Kauf des jeweiligen Produkts**, dessen Marke Ihnen nicht bekannt ist, finanziell *negativ* auswirkt**, z.B. aufgrund von hohen Folgekosten (Reinigung, Reparatur), schlechten Garantiebedingungen oder einfach weil Sie das Produkt vielleicht aus Mangel an Informationen zu einem überhöhten Preis kaufen?
Gebrauchtwagen:

extrem ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ extrem wahrscheinlich

unwahrscheinlich

Zahncreme:

extrem ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ extrem wahrscheinlich
unwahrscheinlich

Kompaktkamera:

extrem ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ extrem wahrscheinlich
unwahrscheinlich

Winterjacke:

extrem ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ extrem wahrscheinlich
unwahrscheinlich

Wie wahrscheinlich ist es, daß Sie für die 4 Produkte, deren Marken Ihnen nicht bekannt sind, die **Leistung bzw. Funktionalitäten** vor dem Kauf über das Internet falsch beurteilen; daß das Produkt also im Endeffekt ***nicht*** das leistet, was Sie sich davon versprechen?

Gebrauchtwagen:

extrem ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ extrem wahrscheinlich
unwahrscheinlich

Zahncreme:

extrem ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ extrem wahrscheinlich
unwahrscheinlich

Kompaktkamera:

extrem ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ extrem wahrscheinlich
unwahrscheinlich

Winterjacke:

extrem ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ extrem wahrscheinlich
unwahrscheinlich

Wie wahrscheinlich ist es, daß Sie unter den 4 Produkten, deren Marken Ihnen nicht bekannt sind, jeweils ein Modell wählen werden, welches **Ihnen** dann vielleicht **langfristig *nicht mehr* wirklich gefällt** oder entspricht?

Gebrauchtwagen:

extrem ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ extrem wahrscheinlich
unwahrscheinlich

Zahncreme:

extrem ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ extrem wahrscheinlich
unwahrscheinlich

Kompaktkamera:

extrem ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ extrem wahrscheinlich
unwahrscheinlich

Winterjacke:

extrem ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ extrem wahrscheinlich
unwahrscheinlich

Wie wahrscheinlich ist es, daß Sie für die 4 Produkte, deren Marken Ihnen nicht bekannt sind, Modelle wählen können, **die bei Ihrer Familie, Ihren Freunden und Bekannten vielleicht *nicht* gut ankommen**?

Gebrauchtwagen:

extrem ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ extrem wahrscheinlich
unwahrscheinlich

Zahncreme:

extrem ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ extrem wahrscheinlich
unwahrscheinlich

Kompaktkamera:

extrem ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ extrem wahrscheinlich
unwahrscheinlich

Winterjacke:

extrem ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ extrem wahrscheinlich
unwahrscheinlich

Stellen Sie sich vor, Sie entscheiden sich, von allen 4 Produkten ein Modell zu kaufen. Wir alle wissen, daß man beim Kauf von unbekannten Produkten auch schon einmal Fehlentscheidungen treffen kann.

Als wie hoch würden Sie den **finanziellen Schaden** empfinden, den Sie eventuell haben könnten, stellte sich heraus, daß Sie die Produkte zu einem überhöhten Preis gekauft haben oder durch Folgekosten oder schlechte Garantiebedingungen etc.Verluste haben?

Gebrauchtwagen?

extrem ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ extrem hoch
gering

Zahncreme?

extrem ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ extrem hoch
gering

Kompaktkamera?

extrem ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ extrem hoch
gering

Winterjacke?

extrem ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ extrem hoch
gering

Als wie hoch empfänden Sie den Schaden, der dadurch entstehen könnte, daß das Produkt eventuell doch **nicht so gut funktioniert**, wie Sie sich das erhoffen?

Gebrauchtwagen?

extrem ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ extrem hoch
gering

Zahncreme?

extrem ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ extrem hoch
gering

Kompaktkamera?

extrem ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ extrem hoch gering

Winterjacke?

extrem ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ extrem hoch
gering
Als wie hoch empfänden Sie den Schaden, der dadurch entstehen könnte, daß das Produkt Ihnen selbst plötzlich nach dem Kauf **nicht mehr gefällt**?

Gebrauchtwagen?

extrem ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ extrem hoch
gering

Zahncreme?

extrem ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ extrem hoch
gering

Kompaktkamera?

extrem ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ extrem hoch
gering

Winterjacke?

extrem ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ extrem hoch
gering

Als wie hoch empfänden Sie den Schaden, der dadurch entstehen könnte, daß das Produkt **bei Ihrer Familie, Freunden und Bekannten gar nicht ankommt**?

Gebrauchtwagen?

extrem ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ extrem hoch
gering

Zahncreme?

extrem ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ extrem hoch
gering

Kompaktkamera?

extrem ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ extrem hoch
gering

Winterjacke?

extrem ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ extrem hoch
gering

Als wie risikoreich sehen Sie es insgesamt an, ein gebrauchtes Auto über das Internet zu kaufen, wenn Sie die Marke nicht kennen?

überhaupt nicht ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ extrem risikoreich
risikoreich

Als wie risikoreich sehen Sie es insgesamt an, Zahncreme über das Internet zu kaufen, wenn Sie die Marke nicht kennen?

überhaupt nicht ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ extrem risikoreich
risikoreich

Als wie risikoreich sehen Sie es insgesamt an, eine Kompaktkamera über das Internet zu kaufen, wenn Sie die Marke nicht kennen

überhaupt nicht ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ extrem risikoreich
risikoreich

Als wie risikoreich sehen Sie es insgesamt an, eine Winterjacke über das Internet zu kaufen, wenn Sie die Marke nicht kennen?

überhaupt nicht ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ extrem risikoreich
risikoreich

Produktnatur (Such-, Erfahrungs- oder Vertrauensgut) (Weiber und Adler, 1995)

In den folgenden Fragen geht es darum zu erforschen, welche Möglichkeiten Sie als Konsument haben, mit Hilfe des Internets die **Qualität** einer Kompaktkamera vor dem Kauf zu beurteilen.

In ein paar Minuten werden Sie möglicherweise eine Kompaktkamera von einem Herstellers kaufen, mit dem Sie bisher noch ***keine*** Erfahrung gemacht haben. Wie zuversichtlich sind Sie, dass Sie mit Hilfe des Internets in der Lage sind, die für Sie wichtigen Qualitätseigenschaften ***vollständig*** zu beurteilen.

gar nicht in der Lage ❍ ❍ ❍ ❍ ❍ ❍ sehr gut in der Lage

Stellen Sie sich vor, Sie hätten die Kamera schon gekauft und bereits ausprobiert. Wie gut fühlen Sie sich jetzt in der Lage, die für Sie wichtigen Qualitätseigenschaften vollständig zu beurteilen.
gar nicht in der Lage ❍ ❍ ❍ ❍ ❍ ❍ sehr gut in der Lage

Geben Sie bitte im folgenden an, ***wie wahrscheinlich*** es ist, daß Sie im Rahmen eines Internetkaufs die für Sie ***wichtigen*** Qualitätseigenschaften vollständig beurteilen können.

Vor dem Kauf der Kompaktkamera kann ich mit Hilfe des Internets die für mich wichtigen Qualitätseigenschaften ***vollständig*** beurteilen
extrem unwahrscheinlich ❍ ❍ ❍ ❍ ❍ ❍ extrem wahrscheinlich

Nach dem Kauf und Gebrauch der Kompaktkamera kann ich die für mich wichtigen Qualitätseigenschaften ***vollständig*** beurteilen

extrem unwahrscheinlich ❍ ❍ ❍ ❍ ❍ ❍ extrem wahrscheinlich

Selbst ***nach*** dem Kauf und Gebrauch der Kompaktkamera kann ich die für mich wichtigen Qualitätseigenschaften ***nicht vollständig*** beurteilen

extrem unwahrscheinlich ❍ ❍ ❍ ❍ ❍ ❍ extrem wahrscheinlich

Schätzen Sie bitte auf einer Skala von 1 - 6 ein, ***wie unsicher*** Sie jetzt ***vor*** dem Kauf einer neuen Kompaktkamera ***insgesamt*** darüber sind, ob sie Ihren Ansprüchen vollständig entsprechen wird.

sehr unsicher ❍ ❍ ❍ ❍ ❍ ❍ überhaupt nicht unsicher

A5b –POST SHOPPING QUESTIONNAIRE

Fragebogen 2 Kamerakauf

Ihre ID?

Als wie angenehm haben Sie den Umgang mit der Suchmaschine empfunden?

sehr angenehm ❍ ❍ ❍ ❍ ❍ ❍ ❍ | ❍ ❍ ❍ ❍ ❍ ❍ ❍ überhaupt nicht angenehm

Warum?.

Und wenn Sie die Suchmaschine als nicht oder überhaupt nicht angenehm empfunden haben (Markierung ‚rechts' vom Strich), hatte das Auswirkungen auf Ihr Interaktionsverhalten mit der Suchmaschine?

❑ ja, hat mein Interaktionsverhalten sehr stark beeinflusst (z.B. zum Abbruch geführt)
❑ ja, hat mein Interaktionsverhalten durchaus beeinflusst
❑ ja, hat mein Interaktionsverhalten leicht beeinflusst
❑ nein, hat mein Interaktionsverhalten kaum beeinflusst
❑ nein, hat mein Interaktionsverhalten gar nicht beeinflusst
❑ bin mir unsicher

Als wie treffend empfanden Sie die Produktvorschläge?

❑ sehr gut zutreffend
❑ gut zutreffend
❑ ausreichend zutreffend
❑ eher weniger zutreffend
❑ gar nicht zutreffend

Im Vergleich zu anderen von Ihnen genutzten Suchmaschinen auf dem Netz (z.B. Altavista, Yahoo, Personalogic etc.), als wie gut empfanden Sie die gerade genutzte Suchmaschine?

❑ erheblich besser
❑ besser
❑ weiss nicht so recht
❑ nicht so gut
❑ schlechter

Warum?...

Jetzt, nachdem Sie auf unserem WWW-Store nach ***einer Kamera*** gesucht und evtl. sogar eine gekauft haben:

Als wie risikoreich sehen Sie es insgesamt an, eine Kompaktkameras über das Internet zu kaufen?

überhaupt nicht risikoreich ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ extrem risikoreich

Wie wahrscheinlich ist es, daß sich Ihre Entscheidung **für die** Kompaktkamera **finanziell *negativ* auswirkt/hätte auswirken können**?

extrem ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ extrem wahrscheinlich

unwahrscheinlich

Wie wahrscheinlich ist es, daß Sie die **Leistung bzw. Funktionalitäten** der Kompaktkameras falsch beurteilt haben, daß das Produkt also im Endeffekt ***nicht*** das leistet, was Sie sich davon versprechen/versprochen hätten?

extrem ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ extrem wahrscheinlich
unwahrscheinlich

Wie wahrscheinlich ist es, daß Sie unter den Kompaktkameras ein Modell gewählt haben oder fast gewählt hätten, welches **Ihnen** dann vielleicht **langfristig *nicht mehr* wirklich gefällt** oder entspricht?

extrem ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ extrem wahrscheinlich
unwahrscheinlich

Wie wahrscheinlich ist es, daß Sie unter den Kompaktkameras ein Modell gewählt haben oder fast gewählt hätten, **welches bei Ihrer Familie, Ihren Freunden und Bekannten vielleicht *nicht* gut ankommt**?

extrem ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ extrem wahrscheinlich
unwahrscheinlich

Ganz ehrlich: Wie würden Sie Ihr eigenes ‚Surf-Verhalten' (Suchverhalten), welches Sie gerade in unserem Onlinestore praktiziert haben, einschätzen? (Jacoby et al., 1978)

❑ ich war nicht so besonders motiviert
❑ ich habe mich nach einem Produkt umgeschaut, was in etwa meinen Bedürfnissen gerecht wird
❑ ich habe mich wirklich bemüht, daß für mich optimale Produkte herauszufinden

Bitte kreuzen Sie den Zustand an, der Ihr Empfinden während des ‚Surfens' am besten beschreibt. *(Csikszentmihaly, M, Csikszentmihaly, I.,1995)*

Herausforderung im
Umgang mit dem niederig ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ hoch
Shopping Interface

Ihre Fähigkeit dasShopping Interface niederig ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ hoch
zu bedienen

Hatten Sie das Gefühl
Sie hätten lieber etwas überhaupt nicht ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ja, auf jeden Fall
anderes gemacht?

Wie gut konnten Sie überhaupt nicht ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ sehr gut
sich konzentrieren?

Wie stark konnten Sie sich selbst vergessen? überhaupt nicht ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ ❍ sehr gut

Haben Sie sich irgendwie körperlich unwohl gefühlt während des ‚Surfens' (z.B. Kopf- oder Gliederschmerzen)? Grad des Wohlbefindens:

❑ mir ging es sehr gut
❑ mir ging es eher gut
❑ mir ging es eher schlecht
❑ mir ging es sehr schlecht

Konnten Sie von der Produktform her auf Marken schließen (z.B. durch das Foto)?

❑ ja
❑ nein
❑ manchmal

Falls ja, haben Sie das Gefühl, daß das Erkennen der Marke Ihr Navigationsverhalten hinterher beeinflusst hat?

❑ ja
❑ nein

Sind Sie bereits mit einer Vorstellung in das Experiment gekommen bzgl. eines Produkts, welches Sie interessieren könnte?

❑ Ja, ich hatte eine klare Vorstellung von dem Produkt, was mich interessiert
❑ Ja, ich hatte eine Vorstellung, war aber noch nicht 100% sicher
❑ Ich hatte mehrere Ideen, welche Produkte mich interessieren könnten
❑ Nein, ich wusste noch gar nicht, welches Produkt mich interessieren würde

A6. Briefing of Participants in the Pre-Study (analysis 3)

Lieber Teilnehmer!

Auf dem Internet werden immer häufiger Suchmaschinen eingesetzt. Dabei gibt es auch solche Suchmaschinen, die dem Konsumenten helfen sollen, das richtige Produkt zu finden (z.B. die richtige Wohnung oder das richtige Auto). Um dem Onlinekunden wirklich zu helfen, müssen Suchmaschinen natürlich Fragen stellen, damit sie wissen, was der Kunde wirklich will. Diese Fragen sind ähnlich denen, die auch ein Verkäufer in einem Geschäft stellen könnte, wenn Kunden das Produkt dort suchen würden. Auf Basis der Antworten sucht die Suchmaschine für den Kunden dann das richtige Produkt in den Internetdatenbanken der Hersteller und Händler.

In der hier anfolgenden Befragung sollt Ihr uns nun helfen, **mögliche Fragen** der Suchmaschine **zu beurteilen und einzuordnen**. Die Fragen sind für 3 Verkaufsszenarien entwickelt worden: den Kauf 1. einer Kompaktkamera, 2. eines sehr hochwertigen Zier-, Radio- oder Reiseweckers und 3. einer Winterjacke.

Für alle Fragen der Suchmaschine soll von Euch beurteilt werden, **1. als wie legitim** und **2. als wie wichtig** Ihr sie im Verkaufskontext anseht. **3.** sollt Ihr für uns einschätzen, als **wie schwierig** Ihr es empfändet, die Frage selbst richtig zu beantworten.

Die Entwicklung der Fragen hat 2 theoretische Hintergründe: 1. die Risikotheorie und 2. die Frage nach Interaktionskosten auf dem Internet. Das bedeutet, daß Ihr zusätzlich zu der Einschätzung von Legitimität, Wichtigkeit und Schwierigkeit noch Angaben machen sollt, **4. welche Interaktionskosten** Ihr für die jeweilige Frage empfindet und **5. in welche Risikokategorie** Ihr sie einordnet.

Dazu solltet Ihr Folgendes wissen:

1. INTERAKTIONSKOSTEN

Die Interaktionskosten stehen hier für **„die intuitive Bereitschaft“** die Frage der Suchmaschine zu beantworten; also das spontane Gefühl, ob man bereit ist, die verlangte private Information von sich preiszugeben. ‚Keine’ Informationskosten bedeuten, daß man überhaupt kein Problem damit hat, die Frage wahrheitsgemäß zu beantworten. ‚Sehr hohe’ Informationskosten stehen dafür, daß man diese Information unter keinen Umständen an eine Suchmaschine weitergeben will.

2. RISIKOTHEORIE

Die Risikotheorie besagt, daß man bei jedem Kauf (und insbesondere beim Kauf hochwertiger Güter) eine Reihe von Risiken wahrnimmt. Diese wahrgenommenen Risiken sind eigentlich nichts anderes als die Angst davor, daß man sich ‚verkaufen’ könnte.

In der Theorie unterteilt man das Gesamtrisiko, sich eventuell zu ‚verkaufen’ vor allem in 2 Bereiche[43]:

1) das funktionale Risiko :

...ist das Risiko, daß das Produkt nicht das leistet, was es verspricht bzw. was Ihr Euch von dem Produkt erhofft. Z.B. wenn ein Auto schon nach kürzester Zeit Reparaturen bedarf oder wenn Ihr bei einer blonden Haartönung hinterher statt blonden ‚braune’ Haare bekommt.

[43] Es gibt noch einen 3.Bereich, den wir hier aber nicht untersuchen möchten. Das ist das finanzielle Risiko.

2) das psycho-soziale Risiko:

...ist das Risiko, daß einem das Produkt nach dem Kauf doch nicht mehr gefällt, und zwar entweder weil es bei Freunden, Bekannten oder der Familie nicht auf Anklang gestoßen ist oder weil man unabhängig von anderen Leuten das Gefühl hat, daß das Produkt irgendwie doch nicht zu einem passt.

Das Programm, mit dessen Hilfe Ihr die Beurteilung der Fragen vornehmen sollt, ist ganz leicht zu bedienen. Links oben steht die potentielle Frage einer Suchmaschine. Darunter stehen die Antworten die ein Konsument zur Verfügung hätte, würde er mit der Suchmaschine kommunizieren. Bitte benutzt beide Informationen, um Euer Urteil zu fällen! Rechts stehen die Skalen, über die Ihr die Beurteilung vornehmen könnt. Ein Klick mit der linken Maustaste auf einen Wert der 5 Skalen genügt für Eure Angaben. Dann geht es über ‚weiter' zur nächsten Frage.

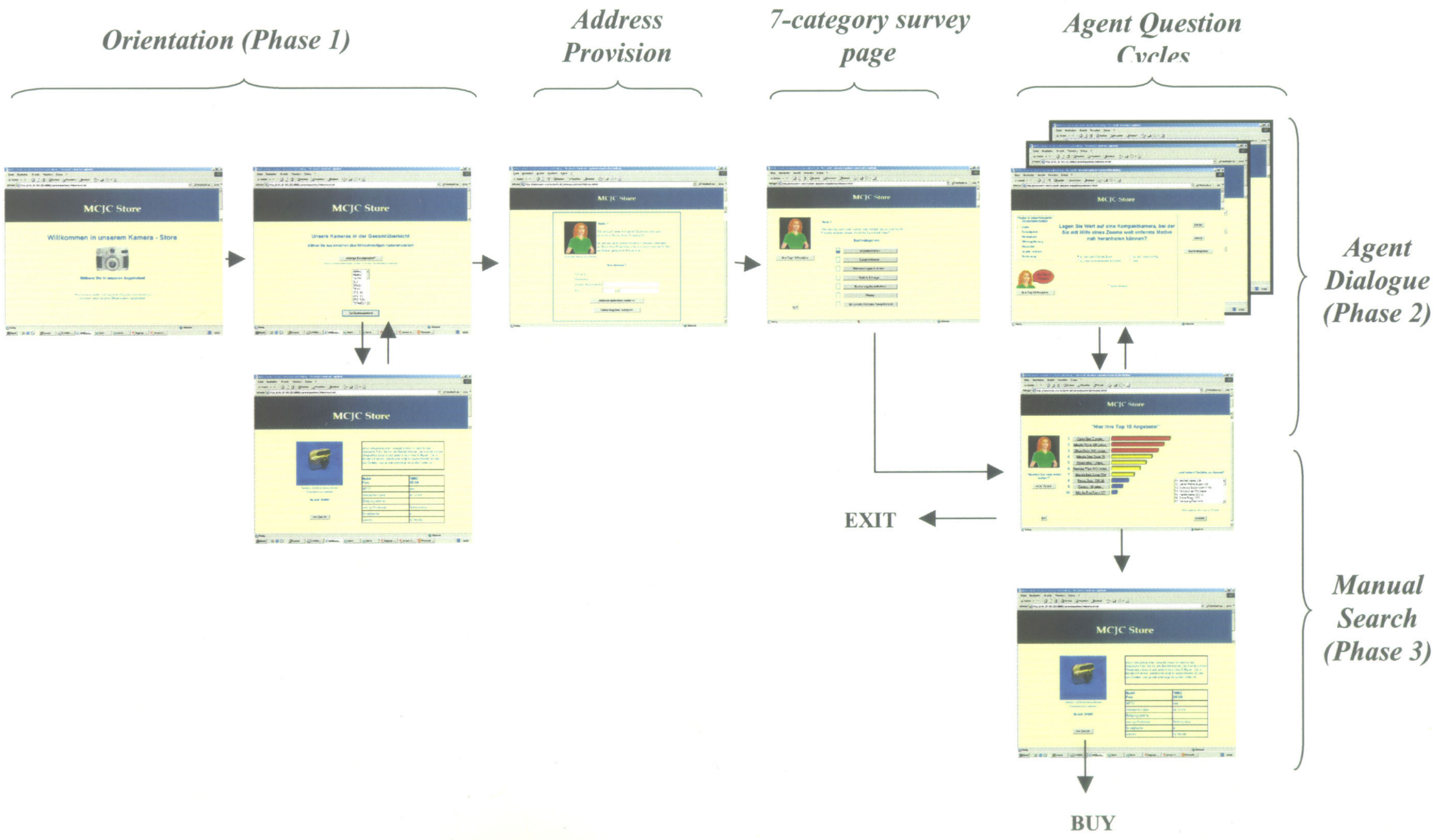
Insgesamt braucht Ihr für die Durchführung wohl ca. 1 ½ Stunden.

Bevor Ihr allerdings damit einsteigt, möchten wir Euch noch einige Fragen zu Eurer Person und Eurer generellen Einstellung bzgl. Online-Privatheit stellen.

Gruß
Euer
IWA-Team!

B – ONLINE MATERIAL

B1a – OVERVIEW OF NAVIGATION



B1b – FULL VIEW OF SCREENS*

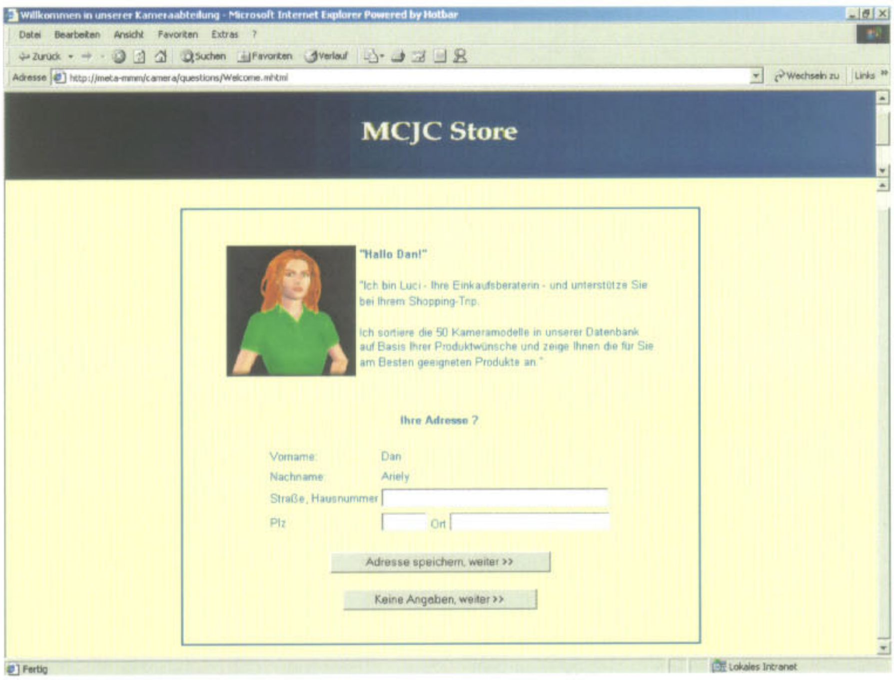
(*see also http://iwa.wiwi.hu-berlin.de to use the store)

➊ Welcome Page

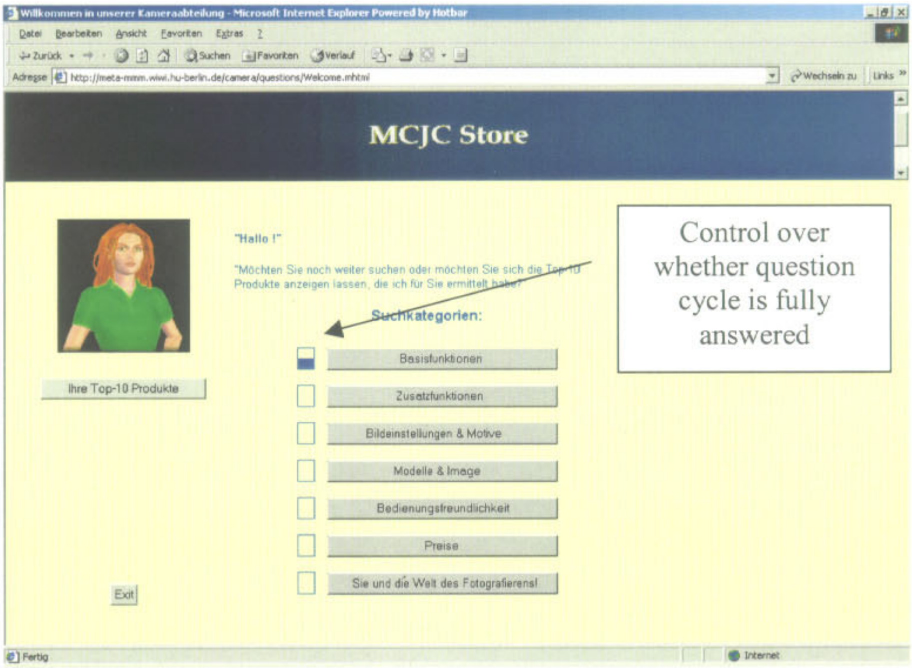
➋ Overview of Products in the Store

❸ **Product Description**: Phase 1; no possibility to buy here

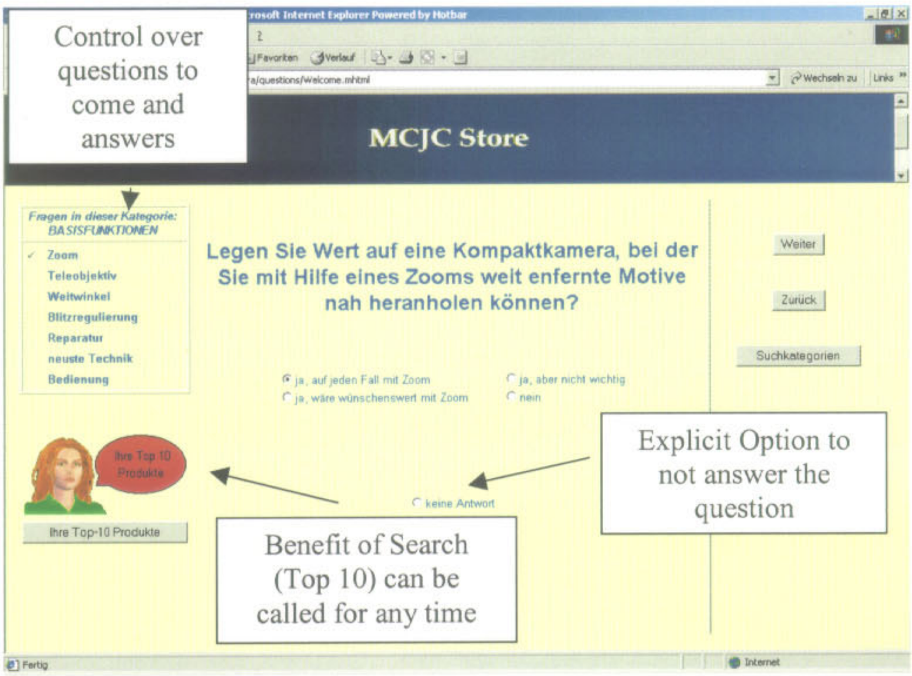
❹ **Luci Introduction:** Agent Luci introduces herself and her purpose to the user; addresses user with his/her first name; gives possibility to leave address (without specifying why)



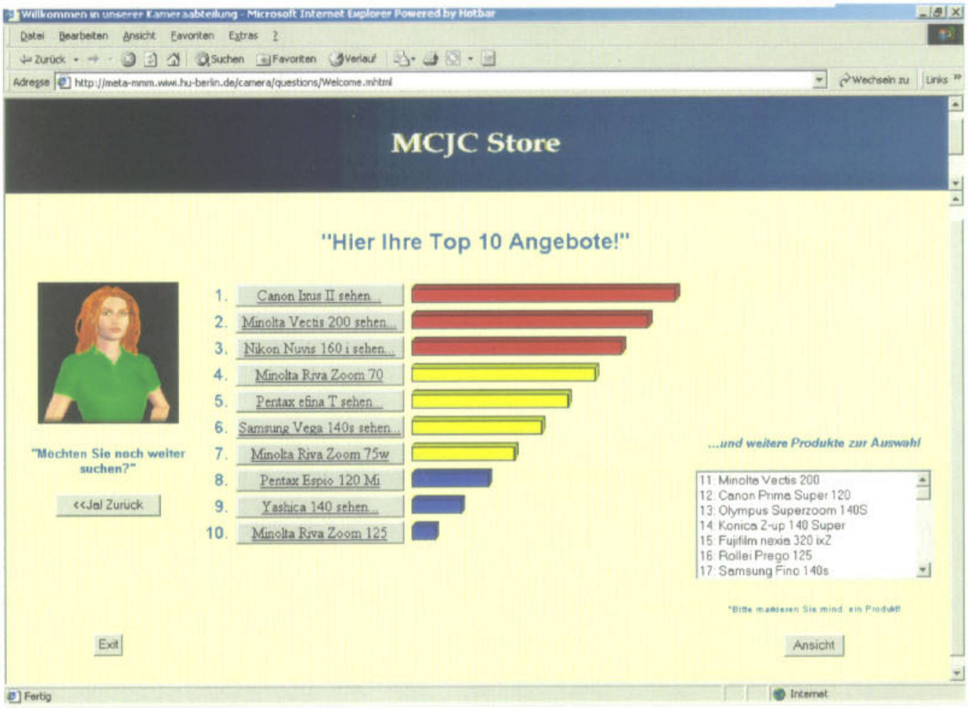
❺ **7-Category Survey Page:** Luci has 7 search categories; all categories contain some relevant information; user is forced to stare at this page for 20 seconds to get the full grasp of potential information exchange; from here Top-10 can be accessed at any time



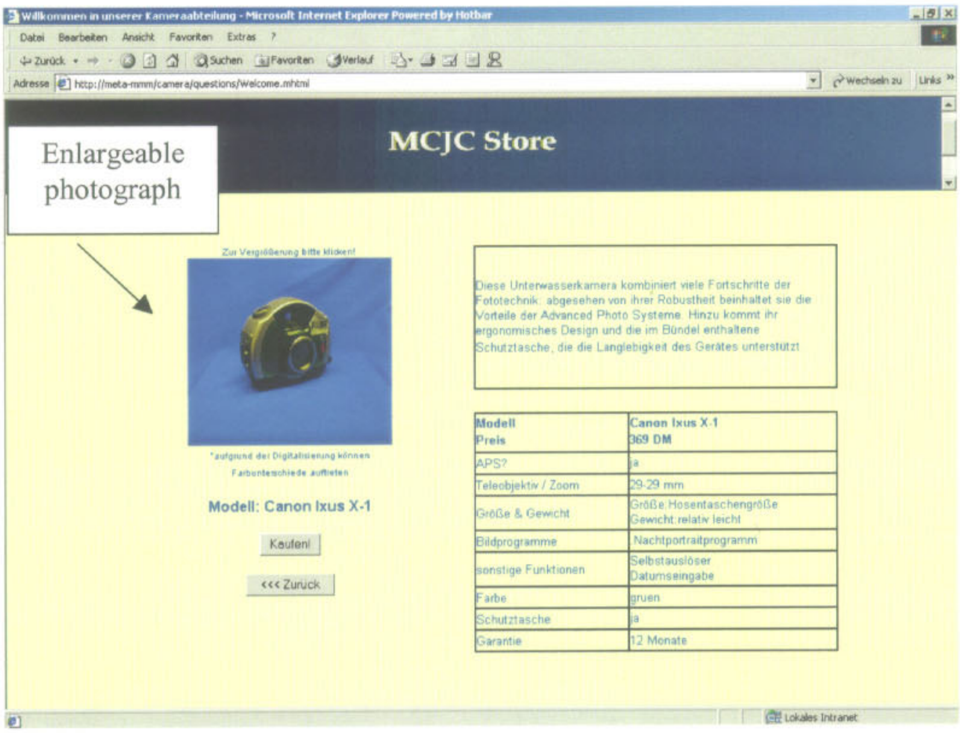
❻ **Exemplary question page:** 56 Questions on a separate page; all questions are related to the purchase context



❼ Top – 10 Ranking of Products: From here, all products can be viewed or search can be continued with the agent



❽ **Detailed Product Description:** From here the user can buy or go back to the Store;



B2. Description of Algorithm behind Luci

(documented by Martin Strobel; International Institute of Infonomics; 10. Mai 2001)

Kodierung der Produkte
Produkte sind in allen relevanten Eigenschaften in einer Datenbank kodiert. Eine numerische Kodierung kann vorteilhaft sein ist aber nicht unbedingt notwendig.
Beispiel Kompaktkamera

Prod Name	Preis	Farbe	Groesse	Zoom-Max	Zoom-Min	Mindest abstand	Blitz eingeb	Bild formate
Canon Prima Super 120	479,-	silber	50	120	35	0,8 m	100	Normal

Anmerkungen:
Farbe wurde nicht numerisch kodiert.

Groesse wurde nicht exakt gemessen, sondern nur grob klassifiziert in sehr groß (100), groß (75), mittel (50), klein (25), sehr klein (0). Analog wurde mit Gewicht verfahren. Eine komplexere Kodierung in Laenge, Hoehe, und Breite bzw. eine exakte Gewichtsangabe wären aber auch denkbar.

Binäre Eigenschaften (wie z.B. Blitz eingebaut?) wurden mit 100 für Ja oder 0 für Nein kodiert.

Einige Eigenschaften wurden direkt mit ihrem numerischen Wert kodiert, z.B. Zoombereich (ZoomMax, ZoomMin), Preis und Mindestabstand.

Kodierung der Antwort
Beispiele von verschiedenen Fragentypen

Frage	Fragentyp	mögliche Antworten	Kodierung
1. Wie wichtig ist Ihnen ein eingebauter Blitz?	Gewichtungsfrage für binäre Eigenschaft	Extrem wichtig	100
		Wichtig	66
		Relativ unwichtig	33
		Egal	0
2. Wie wichtig ist Ihnen ein großes Teleobjektiv?	Gewichtungsfrage für ordinale Eigenschaft	Extrem wichtig	100
		Wichtig	66
		Relativ unwichtig	33
		Egal	0
3. Hätten Sie Lust, an einem Fotowettbewerb teilzunehmen?	Füllfrage, hat keine Auswirkungen auf die Produktempfehlung	Ja, auf jeden Fall	(100)
		Ja, vielleicht	(66)
		Eher nicht	(33)
		Nein, überhaupt nicht	(0)
4. Möchten Sie unterschiedliche Bildformate haben?	Komplexe Frage	Ja, auf jeden Fall (mindestens 3)	100
		Ja, wenn möglich (midestens 2)	66
		Nicht unbedingt nötig	33
		Egal	0

Anmerkungen zur Kodierung der Antworten:

Frage 1, 2 und 4 gehören zu den relevanten Fragen. Die Beantwortung dieser Fragen hat Auswirkungen auf die Empfehlung. Frage 3 ist dafür irrelevant. Die Kodierung wurde daher in Klammern gesetzt.

Die Fragen 1, 2 und 4 unterscheiden sich in der Berechnung der Punkte (siehe weiter unten).

Frage 4 ist eine komplexe Frage. Die Antworten zeichnen bereits gewisse Muster vor. Nachteil von komplexen Fragen ist es, dass gewisse Antworten nicht mehr gegeben werden können (z.B. "Ja , ich möchte auf jeden Fall verschiedene Bildformate haben. Zwei unterschiedliche reichen aber aus.").

Tabellen
Im wesentlichen zielt eine relevante Frage auf eine bestimmte Produkteigenschaft ab. Für jede Frage kann demnach für jedes Produkt bzw. für jede Produkteigenschaft ein Punktwert bestimmt werden. Dies geschieht in Form von Tabellen. Sie sind im System nach Ermessen des Programmierers definiert und hart kodiert worden. Für einen generellen Ansatz ist aber das Ablegen in einer Datenbank mit den geeigneten Werkzeugen für die Wartung notwendig. Sinnvollerweise werden die Tabellen den Fragen zugeordnet.

Beispiel
Die Tabellen für Fragen 2 und 4 können z.B. so aussehen:

Frage 2		**Antwortmöglichkeiten**			
		100	**66**	**33**	**0**
Produkt eigenschaften	**> 120**	**10000**	**6600**	**3300**	**0**
	> 80	**6600**	**6600**	**3300**	**0**
	> 50	**3300**	**3300**	**3300**	**0**
	<= 50	**0**	**0**	**0**	**0**

Frage 4		Antwortmöglichkeiten			
		100	66	33	0
Produkt eigenschaften	Mehrere	10000	6600	3300	0
	Panorama	1000	6600	3300	0
	Normal	0	0	0	0

Formeln

Einige Punkttabellen lassen sich in Form von Formeln kürzer darstellen. So wären

Punkte(Frage 2)	=	Min (Antwort*100, Eigenschaft*100)
Punkte(Frage 1)	=	Antwort * Eigenschaft.

Der Vorteil von Formeln liegt im geringeren Kodierungsaufwand. Im Hinblick auf eine generelle Implementierung verliert man dabei aber an Flexibilität und Allgemeinheit.

Punktsummen

Sobald die Empfehlungsmaschine angestossen wird, wird für jede relevante Frage zu jedem Produkt der entsprechende Punktwert ermittelt. Die ermittelten Punktwerte werden gewichtet und addiert. Am Ende resultiert für jedes Produkt i eine Punktesumme.

Punkte(Prod.i)	=	Punkte(Frage1, Prod.i) * Gewicht (Frage1) * Experimentatorgewichtung (Frage1) + Punkte(Frage2, Prod.i) * Gewicht (Frage2) * Experimentatorgewichtung (Frage2) + Punkte(Frage3, Prod.i) * Gewicht (Frage3) * Experimentatorgewichtung (Frage3) + ...

Je höher sie ist (im Vergleich zu den Punktsummen der anderen Produkte), desto passender ist das Produkt. Die Gewichte entstammen den Ergebnissen der Vorstudie, in der 39 Personen die Wichtigkeit der einzelnen Fragen beurteilten. Die Experimentatorgewichte wurden hinzugefügt um sogenannten KO-Fragen gerecht zu werden. Bei einer herkömmlichen Gewichtung würde der Kunde, der z.B. eine sehr billige Kamera mit sehr vielen teuren Eigenschaften haben will, die teueren Kameras angeboten bekommen, da die Punkte der speziellen Eigenschaften, die Punkte des Preises überwiegen würden. Durch Einführung einer hohen Experimentatorgewichtung für die Preisfrage wird das Problem vehindert. Der dafür entstehende Nachteil, dass die Gewichtung nicht mehr ausschliesslich auf der in der Vorstudie gemessenen Daten beruht, wurde im Gegenzug in Kauf genommen.

Zufallszahlengenerator

Zur Summe der Punkte, die ein Produkt erreichte, wurde noch ein Zufallswert addiert. Dieser war hinreichend klein, so daß dadurch Produkte mit gleicher Punktsumme separiert wurden, die Reihenfolge im wesentlichen aber unbeeinträchtigt blieb. Dieser Zufallswert sollte außerdem verhindern, daß für den Fall von nur wenigen oder keinen Antworten immer die gleichen Produkte in der Empfehlung präsentiert werden.

Empfehlung
Für die Empfehlung wurden die Produkte der Höhe der erreichten Punkte nach geordnet. Absolute Werte sowie relative Werte wurden dabei nicht angegeben.

Akzeptanz
Insgesamt wurden die Empfehlungen als sehr treffend erachtet. Der Hauptkritikpunkt der Versuchspersonen war, dass sie die Gewichtung nicht selbst wählen konnten. Für eine kommerzielle Implementierung wäre eine Änderung in dieser Hinsicht unbedingt notwendig. Fragen bekämen dann grundsätzlich zwei Antwortdimensionen, zum einen die Antwort selbst, zum anderen die Gewichtung, welche die Antwort bei der Ermittlung der Empfehlung spielen soll.

Ein weiterer Kritikpunkt war, dass man keine absoluten oder relativen Werte zur Empfehlung erhält. Man kann also nicht beurteilen, wie sich die Abstände der Produkte zueinander verhalten.

B3. Agent Questions, Perception and Classification

Question-ID	Question Text	Product (j=jacket; k=camera)	Mean-Legitimacy	Mean-Difficulty	Mean-Importance	Mean-Information Cost	Privacy Class	Risk Dimension addressed by the Question
2411	Welche Jackengröße brauchen Sie?	J	09	03	09	02	Pepr	func
2414	Wie stark soll die Jacke am Körper anliegen?	J	08	03	07	02	Pd	soc
2415	Welche Jackenlänge bevorzugen Sie	J	08	03	08	02	Pepr	func
2416	Wie wichtig ist Ihnen die Berücksichtigung von Trendmodellen?	J	07	03	06	03	Pepr	soc
2417	Kaufen Sie regelmäßig dieselben Typen von Jacken?	J	03	03	02	04	Peip	psy
2418	Wenn Sie einen abgesetzten Kragen an der Jacke hätten, welches Material würden Sie bevorzugen?	J	08	03	06	02	Pd	func
2419	Hätten Sie gerne einen abnehmbaren Kragen an der Jacke?	J	08	03	06	01	Pd	func
2421	Für welche Jahreszeiten wollen Sie die Jacke erwerben?	J	09	01	09	01	U	func
2422	Welche Stoffdicke bevorzugen Sie für die Jacke?	J	09	03	08	02	Pd	func
2423	Welchen Anspruch haben Sie an die Wasserdurchlässigkeit des Außenmaterials?	J	09	02	08	01	Pd	func
2424	Welche Außenmaterialien bevorzugen Sie für die Jacke?	J	09	03	09	02	Pd	func
2425	Wie wichtig ist Ihnen die Berücksichtigung von Trendstoffen?	J	06	03	04	03	Pepr	soc
2426	Welche Robustheit erwarten Sie von der Jacke?	J	08	03	07	02	Pd	func
2427	Wie häufig wird die Jacke voraussichtliche getragen werden?	J	04	04	03	05	U	func
2428	Welche Wetterbedingungen herrschen in Ihrer Gegend im Winter?	J	07	03	06	03	Peip	func
2429	Welches Material würden Sie für ein Jackeninnenfutter bevorzugen?	J	09	04	08	02	Pepr	func
2431	Welche Farben kommen für Sie bei der Auswahl der Jacke in Fragen?	J	09	02	09	01	Pd	func

Question-ID	Question Text	Product (j=jacket; k=camera)	Mean-Legitimacy	Mean-Difficulty	Mean-Importance	Mean-Information Cost	Privacy Class	Risk Dimension addressed by the Question
2432	Wie wichtig ist Ihnen die Berücksichtigung von Trendfarben?	J	06	03	05	03	Pepr	soc
2433	Interessieren Sie sich auch für Jacken, die mit einem Muster durchsetzt sind?	J	07	03	06	02	Pepr	func
2434	Wie wichtig ist Ihnen die Vielseitigkeit der Jacke?	J	07	03	06	03	U	func
2435	Als wie stilsicher schätzen Sie sich ein?	J	02	06	02	07	Peip	psy
2436	Was für einen Typ Jacke bevorzugen Sie?	J	08	04	08	02	Pepr	psy
2437	Gibt es an Ihrem Arbeitsplatz eine Kleiderordnung?	J	02	02	02	05	Peip	soc
2438	Wie wichtig ist Ihnen die Vielseitigkeit der Jacke?	J	08	04	07	02	Pd	func
2441	Möchten Sie nutzbare Außentaschen an der Jacke?	J	08	02	07	01	Pd	func
2442	Mögen Sie nicht Taschen als Zierde an Jacken?	J	06	03	04	03	Pepr	soc
2443	Möchten Sie, daß die Jacke ein Innenfutter hat?	J	09	02	07	01	Pd	func
2444	Möchten Sie, daß die Jacke eine Kapuze hat?	J	09	02	08	01	Pd	func
2445	Welche primäre Verschlußart bevorzugen Sie?	J	09	03	08	02	Pepr	func
2446	Möchten Sie ein sichtbares Markenkennzeichen an der Jacke?	J	06	03	05	04	Pd	soc
2447	Wie auffällig sollte die Jacke sein?	J	05	04	04	04	Pd	soc
2448	Mögen Sie es, die Aufmerksamkeit auf sich zu ziehen?	J	02	04	02	07	Peip	psy
2449	Legen Sie Wert darauf, daß es passende Accessoires zur Jacke gi	J	07	03	05	02	Pd	soc
2450	Wie pflegeanfällig darf die Jacke sein?	J	08	02	08	01	Pd	func

Question-ID	Question Text	Product (j=jacket; k=camera)	Mean-Legitimacy	Mean-Difficulty	Mean-Importance	Mean-Information Cost	Privacy Class	Risk Dimension addressed by the Question
2451	Wie häufig wollen Sie Ihre Jacke reinigen?	J	05	04	05	04	U	func
2452	Wie lästig ist es Ihnen, Jacken in die Reinigung zu bringen?	J	03	03	03	05	Peip	psy
2453	Gehen Sie sehr sorgsam mit Ihren Jacken um?	J	02	03	02	06	Peip	psy
2454	Wie häufig kaufen Sie neue Jacken?	J	02	03	02	05	Peip	psy
2455	Wieviele Winterjacken besitzen Sie schon?	J	01	01	01	06	Peip	psy
2456	Empfinden sie eine externe Reinigung als zu teuer?	J	03	03	03	05	Peip	psy
2461	Wieviel Geld sind Sie in etwa bereit, für die Jacke auszugeben?	J	08	03	09	03	Pepr	finan
2462	Bis zu welchem Maximalpreis wollen Sie Angebote bekommen?	J	08	03	08	03	Pepr	finan
2463	Wollen Sie nur Produkte bis zu dem von Ihnen präzisierten Maximalpreis angeboten bekommen?	J	06	03	05	03	Pepr	finan
2464	Wären Sie ggf. bereit, für ein Markenprodukt mehr auszugeben?	J	05	03	04	04	Peip	finan
2471	Wie modebewußt sind Sie?	J	02	04	02	06	Peip	psy
2472	Wird an Ihrem Arbeitsplatz auf Mode geachtet?	J	02	04	02	06	Peip	soc
2473	Legen Sie bei anderen Leuten Wert auf Kleidung?	J	01	03	01	06	Peip	soc
2474	Kaufen Sie auch für ander Kleidung ein?	J	02	02	01	06	Peip	psy
2475	Wo kaufen Sie vorzugsweise Ihre Kleidung?	J	03	03	02	05	Peip	psy
2476	Wie groß ist Ihr Kleidungsbudget pro Saison (inkl. Schuhe)?	J	02	04	02	07	Peip	psy
2477	Versuchen Sie bei modischen Trends auf dem neusten Stand zu bleiben?	J	02	03	02	05	Peip	soc

Question-ID	Question Text	Product (j=jacket; k=camera)	Mean-Legitimacy	Mean-Difficulty	Mean-Importance	Mean-Information Cost	Privacy Class	Risk Dimension addressed by the Question
2478	Suchen Sie Kleidung nach modischen Trends aus?	J	03	03	03	05	Peip	soc
2479	Sind Sie eitel?	J	01	04	01	08	Peip	psy
4211	Legen Sie Wert auf eine Kompaktkamera, bei der Sie mit Hilfe eines Zooms weit enfernte Motive nah heranholen können?	K	09	01	09	01	Pd	func
4212	Wie stark sollte das Teleobjektiv sein?	K	09	05	09	01	Pd	func
4213	Wie stark sollte der Weitwinkel sein?	K	09	05	09	01	Pd	func
4217	Wo soll hauptsächlich fotografiert werden?	K	07	04	06	03	U	func
4218	Sind Sie an den neuesten technischen Möglichkeiten interessiert, die Ihnen eine Kompaktkamera bieten kann ?	K	07	03	07	03	Pepr	func
4219	Als wie kompliziert empfinden Sie die Bedienung von Kompaktkameras?	K	05	03	05	04	Peip	func
4221	Möchten Sie einen Selbstauslöser an der Kompaktkamera?	K	09	01	08	01	Pd	func
4222	Legen Sie Wert auf eine Serienbildschaltung?	K	08	04	07	02	Pd	func
4223	Legen Sie Wert darauf, dass es möglich ist, für das Foto das Datum der Aufnahme festzuhalten ?	K	09	02	07	01	Pd	func
4224	Wie lästig ist Ihnen das 'Hantieren' mit Filmstreifen bei der Nachbestellung von Bildern?	K	04	02	04	04	Pepr	func
4225	Möchten Sie für die Kompaktkamera eine Schutztasche?	K	09	01	08	01	Pd	func
4226	Wollen Sie den Fotoapperat auch für 'Unterwasserbilder' nutzen können?	K	08	02	07	01	U	func
4227	Legen Sie darauf Wert, dass der Fotoapparat eine Dioptrieeinstellung im Sucher erlaubt ?	K	07	04	06	03	Pd	func
4228	Möchten Sie zu dem Fotoapparat ein Stativ benutzen können ?	K	08	02	08	01	Pd	func

Question-ID	Question Text	Product (j=jacket; k=camera)	Mean-Legitimacy	Mean-Difficulty	Mean-Importance	Mean-Information Cost	Privacy Class	Risk Dimension addressed by the Question
4231	Welche Bildprogramme würden Sie gerne zur Verfügung haben?	K	08	04	07	02	Pd	func
4233	Wie wichtig ist Ihnen die Einstellung unterschiedlicher Bildformate?	K	08	03	07	02	Pepr	func
4234	Legen Sie Wert darauf, Objekte aus besonders geringer Entfernung scharf fotografieren zu können ?	K	08	03	07	02	Pepr	func
4235	Zu welchen Anlässen fotografieren Sie meistens/ wollen Sie fotografieren ?	K	04	03	03	04	U	func
4236	Halten Sie sich selbst für einen guten Fotogarfen?	K	02	04	02	07	Peip	psy
4237	Hätten Sie Interesse an Fotowettbewerben mitzumachen?	K	02	02	01	06	Peip	soc
4238	Welche Form von Blitzregulierung wünschen Sie?	K	09	03	08	01	Pd	func
4239	Welche Motive wollen Sie aud Fotos festhalten ?	K	04	04	04	05	U	func
4241	Legen Sie Wert auf ein modisches Design der Kompaktkamera?	K	07	03	06	02	Pd	soc
4242	Wie wichtig ist Ihnen, daß die Kompaktkamera besonders klein ist?	K	08	02	08	01	Pd	func
4243	Wie wichtig ist Ihnen, daß die Kompaktkamera besonders leicht ist?	K	08	02	08	01	Pd	func
4244	Welche Farbgebung bevorzugen Sie für die Kompaktkamera?	K	08	02	06	01	Pd	soc
4245	Welche Art von Objektivverschluß bevorzugen Sie?	K	07	03	05	02	Pd	func
4246	Sind Fotoapparate ein Gesprächsthema, wenn Sie in einer Gruppe von Freunden / Bekannten zusammen sind ?	K	01	02	01	06	Peip	soc
4247	Wie wichtig ist Ihnen, daß die Kompaktkamera bei Ihren Freunden und Bekannten gut ankommt ?	K	02	03	02	07	Peip	soc
4248	Fotografieren Sie selbst oder bitten Sie häufig jemand anderes ein Foto zu machen ?	K	02	02	02	05	U	func

Question-ID	Question Text	Product (j=jacket; k=camera)	Mean-Legitimacy	Mean-Difficulty	Mean-Importance	Mean-Information Cost	Privacy Class	Risk Dimension addressed by the Question
4252	Wie wichtig ist Ihnen die 'Griffigkeit' der Kamera?	K	07	03	06	02	Pd	func
4253	Wie wichtig ist Ihnen ein möglichst einfaches Wechseln der Filme?	K	08	01	07	02	Pepr	func
4254	Haben Sie bereits Erfahrung mit Fotoapparaten ?	K	05	02	04	04	Peip	psy
4255	Wie wichtig ist Ihnen, daß er Apparat auch von Unerfahrenen leicht bedient werden kann?	K	06	02	05	03	U	func
4256	Legen Sie Wert darauf, dass der Fotoapparat von Regen und Schnee nicht beeinträchtigt wird ?	K	08	03	07	02	Pd	func
4258	Wie lange wollen Sie einen heute gekauften Fotoapparat mindestens benutzen können ?	K	05	03	04	04	U	func
4259	Wieviel Garantiezeit wollen Sie mindestens auf den Fotoapperat bekommen?	K	08	02	08	02	Pd	func
4261	Wieviel Geld sind Sie bereit in etwa für den Fotoapparat auszugeben'	K	09	03	09	03	Pepr	finan
4262	Bis zu welchem Maximalpreis möchten Sie Fotoapparate angezeigt bekommen?	K	09	03	09	02	Pepr	finan
4263	Wollen Sie nur Angebote bis zu dem von Ihnen präzisierten Maximalpreis angeboten bekommen?	K	06	03	05	03	Pepr	finan
4264	Wären Sie ggf. bereit, für ein hochwertiges Markenprodukt mehr auszugeben?	K	05	03	05	04	Peip	finan
4265	Wie wichtig sind Ihnen niedrige Kosten bei der Filmentwicklung?	K	07	02	06	03	Pepr	finan
4271	Warum wollen Sie einen Fotoapparat kaufen ?	K	02	02	02	06	Peip	psy
4272	Wie oft fotografieren Sie ?	K	03	03	03	04	U	psy
4273	Welche anderen Kameras besitzen Sie schon?	K	02	01	02	06	Peip	psy
4274	Was ist Ihre Motivation beim fotografieren ?	K	02	03	02	06	Peip	psy
4275	Nehmen Sie relativ viele Fotos auf oder sind Sie eher sparsam mit dem 'knipsen'?	K	03	03	02	05	U	psy

Question-ID	Question Text	Product (j=jacket; k=camera)	Mean-Legitimacy	Mean-Difficulty	Mean-Importance	Mean-Information Cost	Privacy Class	Risk Dimension addressed by the Question
4276	Was machen Sie mit Ihren Fotos?	K	01	02	01	06	Peip	psy
4277	Lassen Sie sich gerne fotografieren ?	K	01	02	01	07	Peip	psy
4278	Halten Sie sich selbst für fotogen?	K	00	04	00	08	Peip	psy
24210	Wie wichtig ist Ihnen das Vorhandensein einer 2. Verschlußart?	J	07	03	05	02	Pepr	func
24410	An welchen Quellen orientieren Sie sich in Sachen Mode?	J	03	04	02	05	Peip	soc
24411	Möchten Sie einen durch einen anderen Stoff 'abgesetzten' Kragen'?	J	07	03	06	02	Pd	func
42210	Wie wichtig ist es Ihnen, daß der Sebstauslöser über eine Fernbedienung ausgelöst werden kann?	K	08	03	07	02	Pd	func
42510	Wie wichtig ist Ihnen eine kleine Tragekordel an dem Apparat?	K	07	02	05	02	Pd	func
42511	Wie wichtig ist Ihnen, daß man den Apparat in Deutschland reparieren lassen kann?	K	08	03	07	02	Pd	func
42512	Wie wichtig ist Ihnen die Robustheit der Kamera	K	09	02	08	02	Pd	func

B4. Rules to formulate Agent Questions

Amount of questions:

There is about the same amount of questions for each product (45 to 50) → the user does not have the impression that he needs to interact less, already because the interface indicates that for one product there is less interaction potential than for another

Structure of questions:

There is an equal amount of 7 question – 'rubriques' the user can search from for each product → again the user does not have the impression that he needs to interact less, already because the interface indicates that for one product there is less interaction potential than for another

The order of questions for all products is determined by the mean-importance of questions tested in advance of the experiment; question importance decreases the 'deeper' a user enters into a search-rubrique → this order is the most realistic, because interface designers/marketers will always seek to minimize user time cost

Rules for the formulation of questions and answers

Questions:

All questions are formulated in such a way that they directly address the user
Products are never expressed as the future product of the user (e.g. 'what do you want <u>your</u> jeans to look like?')
There are two types of questions: 1) where the user is asked to comment specific product traits and 2) where he is asked to reveal something about himself as a person

Answers:

All answers are multiple-choice
The user has the possibility to answer one or more questions
All answers are formulated in such a way that they are comprehensive/intuitive for the user; thus, technical data are only in brackets while easy-to-understand descriptive answers are used
Answers are not limited to yes/no, but are more specific
Eventually answers include the expression of financial sensitivity

B5. Rules to assign Agent Questions to Privacy Classes

We distinguished 4 types of questions related to privacy classes:

pd- questions: non-private

These questions refer directly to the product sought. This is underlined by the article 'the', often used in the formulation of the question. For example, one could ask: "Do you want the jacket to be trendy?" or "How important is a trendy jacket to you?". Only the former question is a 'pd'-question.

pepr – questions : marginally private

These questions refer indirectly to the product, but target more on the consumer. The formulation of the question is vital for this characterization: i.e. one could ask. "What size do you need?" or "What size to you want the jacket to be?". The former question targets the buyer in person, while the latter relates to the specific product sought. Still, the first question, even though personal, is perceived to relate to the product sought. It is therefore a pepr-question (pe=person, pr=product).

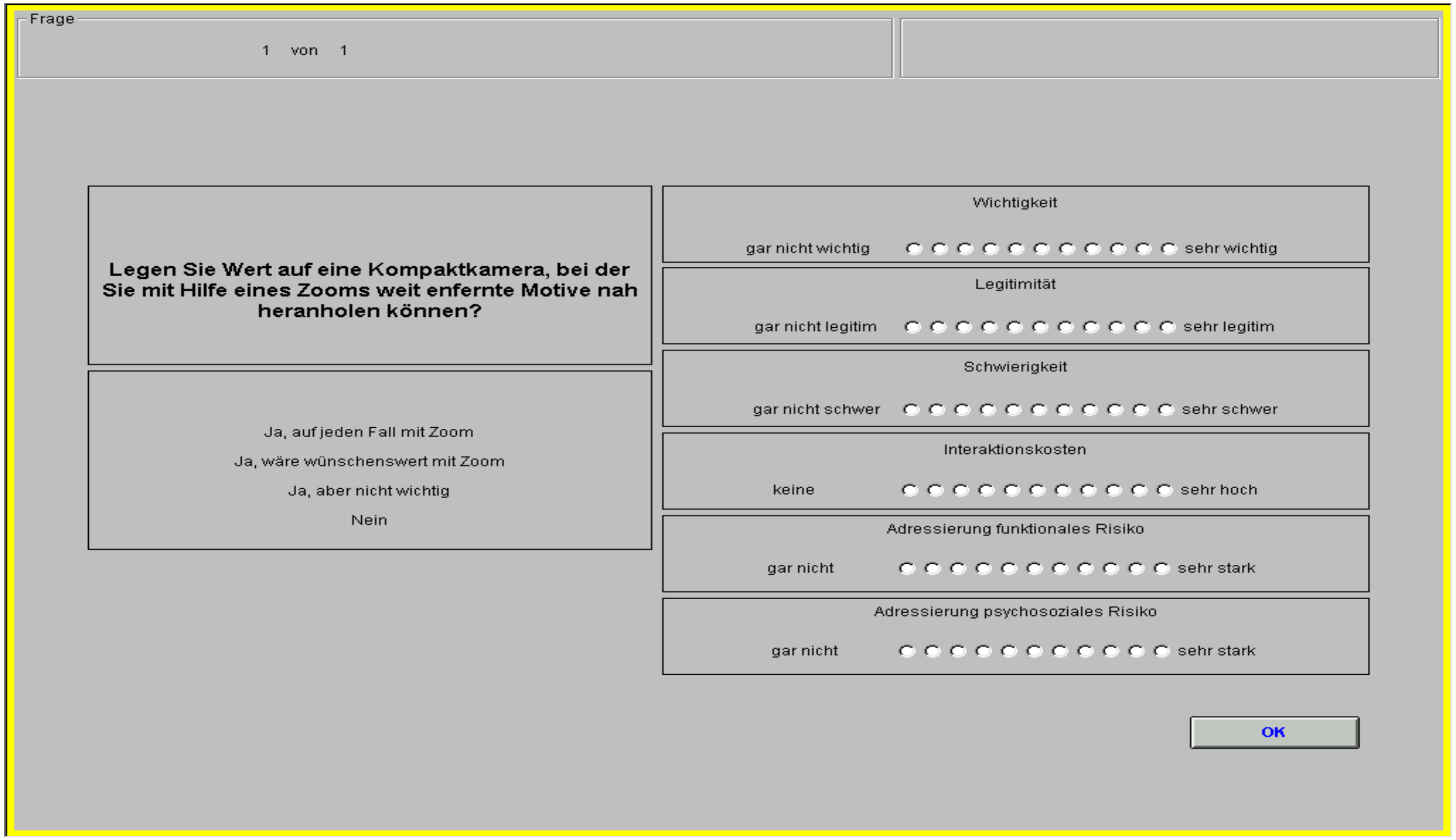
u-questions : relatively private

These questions are related to the person and the usage that is envisioned for the product.

peip-questions : purely private

These questions are of purely personal nature and independent of product selection; thus, they do not allow to select a better product if answered.

B6. Screenshot of Pre-Study Rating Tool



C – DETAILS OF THE ANALYSIS

C1: Measures employed in the Structural Equation Model on Online Information Search

Endogenous Constructs	**Measurement (questions and indices)**
Interaction with Agent	
Number of page requests <zh_int_A>	Standardized value of number of page requests of category survey page, questions and call for Top-10 (transition)
Time spent interacting <zz_int_A>	Standardized value of time spent on category survey page and question pages
Product Inspection	
Number of page requests <zh2_dpd>	Standardized value of number of page requests for products during orientation phase 1 and during detailed inspection phase 3, including photo enlargements and Top-10 pages (excluding transitions)
Time spent 'inspecting' <zz2_dpd>	Standardized value of time spent on phase 1 and phase 3
Perceived product risk before purchase	PL question, e.g. functional risk (n):How probable is it that by buying over the Internet you misjudge the functional performance of any of the 4 products, meaning that the product will not fulfill what it promises? Compact Camera: Very improbable –15 point scale – very probable IL question, e.g. functional risk (n): How strong would be your loss perception in case the product does not perform functionally in the way it is supposed to? Compact Camera: very low – 15 point scale – very high Index: $OPR_j = f\sum_{i=1}^{n}(PL_{ij} \cdot IL_{ij})$

Exogenous Constructs (source of measurement)	Measurement (questions and indices)
Purchase Involvement	**Q1: How important is it for you to find in our online store today and for a 60% discount a compact camera that fulfils your expectations?**

	5 = very important –…- 1 = not at all important Q2: How urgently do you need a compact camera? 4 = very urgently –…- 1 = not at all urgently
Product Class Knowledge (Q1: Srinivasan and Ratchford, 1991; Q2: Moore and Lehmann, 1980)	How strongly fits you the following: Q1: In comparison to the average citizen I already know quite a lot about hifi-equipment (e.g. stereos, cameras, TVs..) Q2: I regularly advise peers in the choice of their electronics…); 5 = very true; 4 = quite true; 3 = depends; 2 = not really; 1 = not at all
Privacy Concern (Ackermann et al., 1999)	When visiting Web sites that collect information, many people find there is some information that they generally feel comfortable providing, some information they feel comfortable providing only under certain conditions, and some information that they never or rarely feel comfortable providing. Please indicate how comfortable you would be to provide each of the following types of information to a Web site. Please check one response for each question: Q1: your first name and family name; Q2: your mail address; Q3: your e-mail address; Q4: your phone number; Q5: information on your computer, hardware and software; Q6: yours yearly income; Q7: your credit card number; Q8: information on your hobbies; Q9: information on your health or medical history; Q10: your age; 5 = I would always feel comfortable providing this information to a Web site. 4 = I would usually feel comfortable providing this information to a Web site. 3 = I would sometimes feel comfortable providing this information to a Web site. 2 =I would rarely feel comfortable providing this information to a Web site. 1 =I would never feel comfortable providing this information to a Web site. $\text{Index}_{\text{Priv}} = (\sum_{in=1}^{10} Q_n) \div 10$
Time Cost	**Q1: Did you have the feeling [while being in the online store] that you had rather done something else?** Not at all – 9point scale – Yes, very much so
Benefit of Interaction	Q1: How well did [Luci] ‘hit’ your needs with her product suggestions? 5 = very well; 4 = quite well; 3 = sufficiently well; 2 = not really well; 1 = not at all

Flow (Csikszentmihalyi et al., 1995)	**Please indicate what feeling corresponds best to the condition that you perceived while you were surfing in the store:** Q1: Challenge in using the shopping interface: low – 9 point scale – high Q2: Your ability to use the shopping interface: low – 9 point scale – high Q3: Did you have the feeling [while being in the online store] that you had rather done something else?**;** Not at all – 9point scale – Yes, very much so Q4: How well could you concentrate? Not at all – 9point scale – very well Q5: How well could you forget yourself? Not at all – 9point scale – very well $\text{Index}_{\text{Flow}} = \left(\sum_{in=1}^{5} Q_n\right) \div 5$
Stage in the Buying Process	Q1: Did you collect any information about the product you signed up for [compact cameras] before you came to us here in the laboratory (e.g. did you go to a store to look at different models?); 1 = yes, I did, 2 = no, I did not Q2: To what extend did you already know what you wanted to buy in the store before you came… Index…

C2: Output of Structural Equation Model on Online Information Search (M-Plus)

```
Mplus VERSION 2.01
MUTHEN & MUTHEN
07/26/2001  10:42 AM

INPUT INSTRUCTIONS

  TITLE:  MSC 2001 (Modell ohne letzterk, mit Effekt von stages auf
          product inspection)

  DATA:
    FILE IS "E:\ANALYSEN\IWA\msc2001\letzte Modellreihe\modell_D.dat";

  VARIABLE:

   NAMES ARE

  AVG10 AUSSAGE AUSSAGE2 KAUFWICH WUNSCH RISK_EMP F2
  F10C STAGES FLOW_B H_INT_A Z_INT_A H2_DPD Z2_DPD;


  USEVARIABLES ARE
    AVG10 AUSSAGE AUSSAGE2 KAUFWICH WUNSCH RISK_EMP F2
  F10C STAGES FLOW_B H_INT_A Z_INT_A H2_DPD Z2_DPD;

  MISSING ARE ALL (-999);

  ANALYSIS:

  ESTIMATOR = MLM;

  MODEL:
   involve BY kaufwich wunsch;
   pknow BY aussage aussage2;
   interaA BY z_int_A h_int_A;
   interaPD BY H2_DPD Z2_DPD;
   risk_emp ON pknow involve stages;
   interaPD ON involve pknow risk_emp f10c f2 flow_b stages;
   interaA ON involve pknow risk_emp f10c flow_b f2
   avg10 stages;
   !h_int_a WITH h2_dpd;
   z2_dpd@0;

  OUTPUT:
  STANDARDIZED;
  modindices;
```

```
  TECH4;


MSC 2001 (Modell ohne letzterk, mit Effekt von stages auf
product inspection)

Mplus VERSION 2.01
MSC 2001 (Modell ohne letzterk, mit Effekt von stages auf

SUMMARY OF ANALYSIS

Number of groups                                 1
Number of observations                         116

Number of y-variables                            9
Number of x-variables                            5
Number of continuous latent variables            4

Observed variables in the analysis
   AVG10       AUSSAGE     AUSSAGE2    KAUFWICH    WUNSCH      RISK_EMP
   F2          F10C        STAGES      FLOW_B      H_INT_A     Z_INT_A
   H2_DPD      Z2_DPD

Continuous latent variables in the analysis
   INVOLVE     PKNOW       INTERAA     INTERAPD


Estimator                                      MLM
Maximum number of iterations                  1000
Convergence criterion                    0.500D-04

Input data file(s)
  E:\ANALYSEN\IWA\msc2001\letzte Modellreihe\modell_D.dat

Input data format  FREE



THE MODEL ESTIMATION TERMINATED NORMALLY



TESTS OF MODEL FIT

Chi-Square Test of Model Fit

          Value                            51.520*
          Degrees of Freedom                   44
          P-Value                          0.2032
          Scaling Correction Factor         1.446
            for MLM
```

```
*  The chi-square value for MLM, MLMV, WLSM and WLSMV cannot be used for
   chi-square difference tests.  MLM chi-square difference testing is
   described on page 360 in the Mplus User's Guide.

Chi-Square Test of Model Fit for the Baseline Model

          Value                             367.485
          Degrees of Freedom                     81
          P-Value                            0.0000

CFI/TLI

          CFI                                 0.974
          TLI                                 0.952
Mplus VERSION 2.01

MSC 2001 (Modell ohne letzterk, mit Effekt von stages auf


RMSEA (Root Mean Square Error Of Approximation)

          Estimate                            0.038

SRMR (Standardized Root Mean Square Residual)

          Value                               0.053

WRMR (Weighted Root Mean Square Residual)

          Value                               0.796




MODEL RESULTS

                   Estimates     S.E.  Est./S.E.    Std     StdYX

 INVOLVE  BY
    KAUFWICH           1.000    0.000      0.000    1.026    0.953
    WUNSCH             0.492    0.088      5.605    0.505    0.656

 PKNOW    BY
    AUSSAGE            1.000    0.000      0.000    1.041    0.989
    AUSSAGE2           0.721    0.124      5.829    0.751    0.662

 INTERAA  BY
    Z_INT_A            1.000    0.000      0.000    1.896    0.921
    H_INT_A            0.886    0.186      4.775    1.680    0.675
```

```
 INTERAPD BY
    H2_DPD             1.000    0.000      0.000    4.526    0.791
    Z2_DPD             0.951    0.087     10.875    4.306    1.000

 INTERAPD ON
    INVOLVE            1.620    0.442      3.664    0.367    0.367
    PKNOW              0.024    0.458      0.052    0.005    0.005

 INTERAA  ON
    INVOLVE            0.582    0.229      2.539    0.315    0.315
    PKNOW             -0.684    0.232     -2.946   -0.375   -0.375

 INTERAPD ON
    RISK_EMP           0.436    0.259      1.685    0.096    0.139
    F10C              -0.646    0.178     -3.633   -0.143   -0.299
    F2                -0.094    0.473     -0.198   -0.021   -0.018
    FLOW_B             0.684    0.390      1.753    0.151    0.164
    STAGES            -0.440    0.577     -0.762   -0.097   -0.059

 INTERAA  ON
    RISK_EMP          -0.029    0.117     -0.250   -0.015   -0.022
    F10C              -0.146    0.094     -1.545   -0.077   -0.161
    FLOW_B             0.266    0.169      1.574    0.140    0.152
    F2                -0.409    0.248     -1.650   -0.216   -0.190
    AVG10             -0.782    0.283     -2.769   -0.412   -0.259
    STAGES            -0.241    0.292     -0.828   -0.127   -0.077
Mplus VERSION 2.01



MSC 2001 (Modell ohne letzterk, mit Effekt von stages auf



 RISK_EMP ON
    PKNOW             -0.320    0.156     -2.057   -0.334   -0.232
    INVOLVE            0.023    0.146      0.158    0.024    0.016

 RISK_EMP ON
    STAGES            -0.193    0.207     -0.932   -0.193   -0.081

 PKNOW    WITH
    INVOLVE            0.380    0.111      3.415    0.355    0.355

 INTERAPD WITH
    INTERAA            1.836    0.782      2.349    0.214    0.214

 AVG10    WITH
    INVOLVE            0.062    0.058      1.074    0.061    0.096
    PKNOW             -0.035    0.054     -0.647   -0.033   -0.053

 F2       WITH
```

```
   INVOLVE            0.006    0.074      0.085    0.006    0.007
   PKNOW             -0.063    0.072     -0.867   -0.060   -0.068

 F10C     WITH
   INVOLVE            0.202    0.232      0.870    0.197    0.094
   PKNOW             -0.096    0.199     -0.482   -0.092   -0.044

 STAGES   WITH
   INVOLVE            0.113    0.054      2.081    0.110    0.182
   PKNOW              0.134    0.052      2.554    0.129    0.213

 FLOW_B   WITH
   INVOLVE           -0.031    0.101     -0.309   -0.031   -0.028
   PKNOW              0.066    0.091      0.729    0.064    0.059

 Residual Variances
   AUSSAGE            0.025    0.163      0.152    0.025    0.022
   AUSSAGE2           0.723    0.135      5.356    0.723    0.562
   KAUFWICH           0.106    0.160      0.664    0.106    0.092
   WUNSCH             0.338    0.060      5.613    0.338    0.569
   RISK_EMP           1.938    0.226      8.577    1.938    0.935
   H_INT_A            3.378    0.546      6.187    3.378    0.545
   Z_INT_A            0.642    0.575      1.116    0.642    0.152
   H2_DPD            12.255    2.175      5.634   12.255    0.374
   Z2_DPD             0.000    0.000      0.000    0.000    0.000
   INTERAA            2.848    0.763      3.734    0.792    0.792
   INTERAPD          16.510    3.630      4.549    0.806    0.806

 Variances
   INVOLVE            1.053    0.221      4.760    1.000    1.000
   PKNOW              1.083    0.190      5.698    1.000    1.000

 Intercepts
   AUSSAGE            3.647    0.095     38.581    3.647    3.465
   AUSSAGE2           2.845    0.102     27.757    2.845    2.508
   KAUFWICH           3.353    0.097     34.496    3.353    3.114
   WUNSCH             2.362    0.071     33.186    2.362    3.067
   RISK_EMP           3.525    0.385      9.149    3.525    2.448
Mplus VERSION 2.01


MSC 2001 (Modell ohne letzterk, mit Effekt von stages auf

   H_INT_A           11.280    1.877      6.011   11.280    4.530
   Z_INT_A           11.148    1.937      5.755   11.148    5.415
   H2_DPD             7.796    3.057      2.550    7.796    1.363
   Z2_DPD             7.051    2.854      2.471    7.051    1.638


R-SQUARE

   Observed
```

Variable	R-Square
AUSSAGE	0.978
AUSSAGE2	0.438
KAUFWICH	0.908
WUNSCH	0.431
RISK_EMP	0.065
H_INT_A	0.455
Z_INT_A	0.848
H2_DPD	0.626
Z2_DPD	1.000

Latent Variable	R-Square
INTERAA	0.208
INTERAPD	0.194

TECHNICAL 4 OUTPUT

ESTIMATES DERIVED FROM THE MODEL

ESTIMATED MEANS FOR THE LATENT VARIABLES

	INVOLVE	PKNOW	INTERAA	INTERAPD	RISK_EMP
1	0.000	0.000	-3.757	0.419	3.207

ESTIMATED MEANS FOR THE LATENT VARIABLES

	AVG10	F2	F10C	STAGES	FLOW_B
1	3.310	3.397	6.534	1.647	6.260

ESTIMATED COVARIANCE MATRIX FOR THE LATENT VARIABLES

	INVOLVE	PKNOW	INTERAA	INTERAPD	RISK_EMP
INVOLVE	1.053				
PKNOW	0.380	1.083			
INTERAA	0.241	-0.457	3.596		
INTERAPD	1.461	0.536	2.558	20.485	
RISK_EMP	-0.119	-0.364	0.118	0.717	2.073
AVG10	0.062	-0.035	-0.194	0.158	0.008
F2	0.006	-0.063	-0.138	-0.205	0.031
F10C	0.202	-0.096	-0.248	-1.854	0.031

Mplus VERSION 2.01

MSC 2001 (Modell ohne letzterk, mit Effekt von stages auf

STAGES	0.113	0.134	-0.116	-0.052	-0.111
FLOW_B	-0.031	0.066	0.100	0.065	-0.017

ESTIMATED COVARIANCE MATRIX FOR THE LATENT VARIABLES

	AVG10	F2	F10C	STAGES	FLOW_B
AVG10	0.395				
F2	-0.162	0.774			
F10C	-0.231	0.590	4.387		
STAGES	0.023	-0.058	0.025	0.366	
FLOW_B	-0.146	0.293	1.033	-0.025	1.177

ESTIMATED CORRELATION MATRIX FOR THE LATENT VARIABLES

	INVOLVE	PKNOW	INTERAA	INTERAPD	RISK_EMP
INVOLVE	1.000				
PKNOW	0.355	1.000			
INTERAA	0.124	-0.232	1.000		
INTERAPD	0.315	0.114	0.298	1.000	
RISK_EMP	-0.081	-0.243	0.043	0.110	1.000
AVG10	0.096	-0.053	-0.163	0.055	0.009
F2	0.007	-0.068	-0.083	-0.051	0.025
F10C	0.094	-0.044	-0.062	-0.196	0.010
STAGES	0.182	0.213	-0.101	-0.019	-0.127
FLOW_B	-0.028	0.059	0.049	0.013	-0.011

ESTIMATED CORRELATION MATRIX FOR THE LATENT VARIABLES

	AVG10	F2	F10C	STAGES	FLOW_B
AVG10	1.000				
F2	-0.293	1.000			
F10C	-0.176	0.320	1.000		
STAGES	0.059	-0.109	0.020	1.000	
FLOW_B	-0.215	0.307	0.455	-0.038	1.000

Beginning Time: 10:42:59
Ending Time: 10:43:00
Elapsed Time: 00:00:01

```
Web: www.StatModel.com
Support: Support@StatModel.com

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C3: Output of Structural Equation Model on Private Consumer Information Cost (M-Plus)

C3a: Total sample

```
Mplus VERSION 1.04
MUTHEN & MUTHEN
02/05/2001   2:06 PM

INPUT INSTRUCTIONS

  TITLE: Simultanes Mehrgleichungsmodell fuer die Beziehung
  zwischen IC, LEG, WICH und SCHW (mit WICH --> LEG)

  Stichprobe: alle Fragen, disaggregrierte Daten

  DATA: FILE IS dummy_all.dat;

  VARIABLE: NAMES ARE

  LEG SCHW WICH IC
  P1DUMMY P2DUMMY P3DUMMY P4DUMMY P5DUMMY P6DUMMY P8DUMMY P9DUMMY P10DUMMY
  P11DUMMY P12DUMMY P13DUMMY P14DUMMY P15DUMMY P16DUMMY P17DUMMY P18DUMMY
  P19DUMMY P20DUMMY P21DUMMY P22DUMMY P23DUMMY P24DUMMY        P25DUMMY P26DUMMY
  P27DUMMY P28DUMMY P29DUMMY P30DUMMY P31DUMMY P32DUMMY P33DUMMY P34DUMMY
  P35DUMMY P36DUMMY P37DUMMY P38DUMMY P39DUMMY;

  USEVARIABLES IC LEG WICH SCHW
  P2DUMMY P3DUMMY P4DUMMY P5DUMMY P6DUMMY P8DUMMY P9DUMMY P10DUMMY
  P11DUMMY P12DUMMY P13DUMMY P14DUMMY P15DUMMY P16DUMMY P17DUMMY P18DUMMY
  P19DUMMY P20DUMMY P21DUMMY P22DUMMY P23DUMMY P24DUMMY        P25DUMMY P26DUMMY
  P27DUMMY P28DUMMY P29DUMMY P30DUMMY P31DUMMY P32DUMMY P33DUMMY P34DUMMY
  P35DUMMY P36DUMMY P37DUMMY P38DUMMY P39DUMMY;

  ANALYSIS: TYPE IS MEANSTRUCTURE;

  MODEL:
      ic ON leg wich schw
      P2DUMMY P3DUMMY P4DUMMY P5DUMMY P6DUMMY P8DUMMY P9DUMMY P10DUMMY
      P11DUMMY P12DUMMY P13DUMMY P14DUMMY P15DUMMY P16DUMMY P17DUMMY P18DUMMY
      P19DUMMY P20DUMMY P21DUMMY P22DUMMY P23DUMMY P24DUMMY P25DUMMY P26DUMMY
      P27DUMMY P28DUMMY P29DUMMY P30DUMMY P31DUMMY P32DUMMY P33DUMMY P34DUMMY
      P35DUMMY P36DUMMY P37DUMMY P38DUMMY P39DUMMY;
      leg ON wich
      P2DUMMY P3DUMMY P4DUMMY P5DUMMY P6DUMMY P8DUMMY P9DUMMY P10DUMMY
```

```
    P11DUMMY P12DUMMY P13DUMMY P14DUMMY P15DUMMY P16DUMMY P17DUMMY P18DUMMY
    P19DUMMY P20DUMMY P21DUMMY P22DUMMY P23DUMMY P24DUMMY P25DUMMY P26DUMMY
    P27DUMMY P28DUMMY P29DUMMY P30DUMMY P31DUMMY P32DUMMY P33DUMMY P34DUMMY
    P35DUMMY P36DUMMY P37DUMMY P38DUMMY P39DUMMY;
    [ic leg];

OUTPUT:
   Tech4;
   Tech3;
```

```
Mplus VERSION 1.04                                                    PAGE    2



INPUT READING TERMINATED NORMALLY



Simultanes Mehrgleichungsmodell fuer die Beziehung
zwischen IC, LEG, WICH und SCHW (mit WICH --> LEG)

Stichprobe: alle Fragen, disaggregrierte Daten

SUMMARY OF ANALYSIS
Mplus VERSION 1.04                                                    PAGE    3
Simultanes Mehrgleichungsmodell fuer die Beziehung


Number of groups                                 1
Number of observations                        4256

Number of y-variables                            2
Number of x-variables                           39
Number of continuous latent variables            0

Observed variables in the analysis
   IC          LEG         WICH        SCHW        P2DUMMY     P3DUMMY
   P4DUMMY     P5DUMMY     P6DUMMY     P8DUMMY     P9DUMMY     P10DUMMY
   P11DUMMY    P12DUMMY    P13DUMMY    P14DUMMY    P15DUMMY    P16DUMMY
   P17DUMMY    P18DUMMY    P19DUMMY    P20DUMMY    P21DUMMY    P22DUMMY
   P23DUMMY    P24DUMMY    P25DUMMY    P26DUMMY    P27DUMMY    P28DUMMY
   P29DUMMY    P30DUMMY    P31DUMMY    P32DUMMY    P33DUMMY    P34DUMMY
   P35DUMMY    P36DUMMY    P37DUMMY    P38DUMMY    P39DUMMY


Estimator                                       ML
Maximum number of iterations                  1000
Convergence criterion                    .500D-04

Input data file(s)
  dummy_all.dat

Input data format  FREE



THE MODEL ESTIMATION TERMINATED NORMALLY
```

```
TESTS OF MODEL FIT

Chi-Square Test of Model Fit

          Value                      1.864
          Degrees of Freedom             1
          P-Value                    .1722

Loglikelihood

          H0 Value               32004.760
          H1 Value               32005.692

Information Criteria

          Number of Free Parameters              82
          Akaike (AIC)                   -63845.520
          Bayesian (BIC)                 -63324.321
          Sample-Size Adjusted BIC       -63584.883
            (n* = (n + 2) / 24)

RMSEA (Root Mean Square Error Of Approximation)

          Estimate                    .014
```



```
          90 Percent C.I.             .000    .046
          Probability RMSEA <= .05    .971



MODEL RESULTS

                   Estimates     S.E.  Est./S.E.

 IC        ON
    LEG                -.559     .017    -33.334
    WICH               -.010     .017      -.589
    SCHW                .138     .014      9.931
    P2DUMMY           -1.253     .279     -4.492
    P3DUMMY            1.864     .280      6.651
    P4DUMMY             .512     .283      1.813
    P5DUMMY           -3.194     .282    -11.337
    P6DUMMY             .424     .281      1.508
    P8DUMMY             .041     .279       .148
    P9DUMMY            1.175     .280      4.199
    P10DUMMY          -1.137     .279     -4.067
    P11DUMMY           -.713     .286     -2.492
    P12DUMMY            .610     .280      2.178
```

P13DUMMY	1.531	.279	5.494
P14DUMMY	-.739	.278	-2.661
P15DUMMY	-1.789	.278	-6.426
P16DUMMY	-1.500	.279	-5.375
P17DUMMY	.516	.282	1.825
P18DUMMY	-2.910	.279	-10.416
P19DUMMY	-3.861	.282	-13.704
P20DUMMY	.541	.280	1.929
P21DUMMY	-.118	.279	-.422
P22DUMMY	-.019	.280	-.067
P23DUMMY	-1.390	.282	-4.923
P24DUMMY	-.128	.279	-.460
P25DUMMY	1.381	.278	4.959
P26DUMMY	-1.209	.279	-4.337
P27DUMMY	.684	.278	2.457
P28DUMMY	-.809	.279	-2.902
P29DUMMY	.482	.281	1.715
P30DUMMY	-4.318	.282	-15.289
P31DUMMY	.248	.282	.878
P32DUMMY	-1.572	.279	-5.635
P33DUMMY	-.893	.279	-3.198
P34DUMMY	-1.284	.278	-4.620
P35DUMMY	-.711	.280	-2.544
P36DUMMY	.429	.282	1.521
P37DUMMY	1.737	.282	6.149
P38DUMMY	1.342	.279	4.809
P39DUMMY	.821	.279	2.947
LEG ON			
WICH	.875	.009	101.396
P2DUMMY	-.113	.254	-.444
P3DUMMY	.119	.256	.465
P4DUMMY	.110	.258	.427
P5DUMMY	1.271	.256	4.959

P6DUMMY	2.477	.254	9.738
P8DUMMY	.373	.254	1.468
P9DUMMY	-.530	.254	-2.086
P10DUMMY	.871	.255	3.416
P11DUMMY	3.740	.255	14.668
P12DUMMY	1.298	.255	5.087
P13DUMMY	-.929	.254	-3.660
P14DUMMY	.328	.254	1.294
P15DUMMY	-.396	.254	-1.559
P16DUMMY	.920	.255	3.613
P17DUMMY	-.453	.257	-1.763
P18DUMMY	.376	.255	1.475
P19DUMMY	.102	.256	.398
P20DUMMY	-.211	.255	-.826
P21DUMMY	-.408	.255	-1.600
P22DUMMY	.006	.256	.025
P23DUMMY	1.415	.256	5.535
P24DUMMY	.759	.254	2.985
P25DUMMY	.472	.254	1.854
P26DUMMY	.074	.255	.291
P27DUMMY	.214	.254	.841
P28DUMMY	-.859	.254	-3.377
P29DUMMY	1.578	.256	6.165
P30DUMMY	1.212	.257	4.715
P31DUMMY	.365	.256	1.426
P32DUMMY	-.138	.255	-.542
P33DUMMY	.368	.255	1.442
P34DUMMY	.091	.254	.358
P35DUMMY	.312	.255	1.222
P36DUMMY	1.058	.257	4.112
P37DUMMY	-.787	.255	-3.082
P38DUMMY	.436	.255	1.709
P39DUMMY	.225	.254	.884
Residual Variances			
IC	4.314	.094	46.130
LEG	3.605	.078	46.130
Intercepts			
IC	6.649	.216	30.848
LEG	.876	.193	4.549

TECHNICAL 3 OUTPUT

ESTIMATED COV. MATRIX FOR PARAMETER ESTIMATES

1	2	3	4	5

1	.046				
2	.000	.037			
3	.000	.000	.000		
4	-.001	.000	.000	.000	
5	-.001	.000	.000	.000	.000
6	-.041	.000	.000	.000	.000
7	-.042	.000	.000	.000	.000
8	-.043	.000	.000	.001	.000
9	-.042	.000	.000	.001	.000
10	-.040	.000	-.001	.001	.000
11	-.039	.000	.000	.000	.000
12	-.039	.000	.000	.000	.000
13	-.040	.000	.000	.000	.000
14	-.039	.000	-.001	.001	.000
15	-.041	.000	.000	.001	.000
16	-.040	.000	.000	.000	.000
17	-.040	.000	.000	.000	.000
18	-.040	.000	.000	.000	.000
19	-.040	.000	.000	.000	.000
20	-.041	.000	.000	.000	.000
21	-.041	.000	.000	.000	.000
22	-.043	.000	.000	.000	.000
23	-.040	.000	.000	.000	.000
24	-.041	.000	.000	.000	.000
25	-.041	.000	.000	.000	.000
26	-.042	.000	.000	.001	.000
27	-.039	.000	.000	.000	.000
28	-.040	.000	.000	.000	.000
29	-.041	.000	.000	.000	.000
30	-.040	.000	.000	.000	.000
31	-.040	.000	.000	.000	.000
32	-.041	.000	.000	.001	.000
33	-.041	.000	.000	.001	.000
34	-.040	.000	.000	.000	.000
35	-.040	.000	.000	.000	.000
36	-.040	.000	.000	.000	.000
37	-.039	.000	.000	.000	.000
38	-.040	.000	.000	.000	.000
39	-.042	.000	.000	.001	.000
40	-.039	.000	.000	.000	-.001
41	-.041	.000	.000	.000	.000
42	-.040	.000	.000	.000	.000
43	.000	-.001	.000	.000	.000
44	.000	-.033	.000	.000	.000
45	.000	-.035	.000	.000	.000
46	.000	-.035	.000	.000	.000
47	.000	-.035	.000	.000	.000
48	.000	-.033	.000	.000	.000
49	.000	-.034	.000	.000	.000
50	.000	-.033	.000	.000	.000
51	.000	-.034	.000	.000	.000

52	.000	-.034	.000	.000	.000
53	.000	-.034	.000	.000	.000
54	.000	-.033	.000	.000	.000
55	.000	-.033	.000	.000	.000
56	.000	-.033	.000	.000	.000
57	.000	-.034	.000	.000	.000
58	.000	-.035	.000	.000	.000
59	.000	-.034	.000	.000	.000
60	.000	-.035	.000	.000	.000
61	.000	-.034	.000	.000	.000
62	.000	-.034	.000	.000	.000
63	.000	-.035	.000	.000	.000
64	.000	-.034	.000	.000	.000
65	.000	-.033	.000	.000	.000
66	.000	-.034	.000	.000	.000
67	.000	-.034	.000	.000	.000
68	.000	-.033	.000	.000	.000
69	.000	-.033	.000	.000	.000
70	.000	-.035	.000	.000	.000
71	.000	-.035	.000	.000	.000
72	.000	-.035	.000	.000	.000
73	.000	-.034	.000	.000	.000
74	.000	-.034	.000	.000	.000
75	.000	-.033	.000	.000	.000
76	.000	-.034	.000	.000	.000
77	.000	-.035	.000	.000	.000
78	.000	-.034	.000	.000	.000
79	.000	-.034	.000	.000	.000
80	.000	-.034	.000	.000	.000
81	.000	.000	.000	.000	.000
82	.000	.000	.000	.000	.000

ESTIMATED COV. MATRIX FOR PARAMETER ESTIMATES

	6	7	8	9	10
6	.078				
7	.039	.079			
8	.040	.041	.080		
9	.040	.040	.041	.079	
10	.039	.039	.040	.040	.079
11	.039	.039	.039	.039	.039
12	.038	.039	.039	.038	.038
13	.039	.039	.040	.040	.040
14	.039	.040	.040	.041	.042
15	.039	.040	.040	.040	.040
16	.039	.039	.039	.039	.038
17	.039	.039	.039	.039	.039
18	.039	.039	.040	.039	.039
19	.039	.039	.040	.040	.040
20	.039	.040	.040	.040	.039
21	.039	.040	.040	.040	.039

22	.040	.040	.041	.041	.040
23	.039	.039	.040	.039	.039
24	.039	.040	.040	.040	.039
25	.039	.040	.040	.040	.039
26	.040	.040	.041	.041	.040
27	.039	.039	.039	.039	.039
28	.039	.039	.040	.039	.039
29	.039	.040	.040	.040	.039
30	.039	.039	.039	.039	.039
31	.039	.039	.039	.039	.038
32	.039	.040	.040	.040	.040
33	.039	.040	.041	.040	.040
34	.039	.040	.040	.040	.039
35	.039	.039	.040	.039	.039
36	.039	.039	.040	.039	.039
37	.038	.039	.039	.039	.039
38	.039	.039	.040	.039	.039
39	.039	.040	.041	.041	.040
40	.038	.039	.039	.039	.038
41	.039	.040	.040	.040	.039
42	.039	.039	.039	.039	.039
43	.000	.000	.000	.000	.000
44	.000	.000	.000	.000	.000
45	.000	.000	.000	.000	.000
46	.000	.000	.000	.000	.000
47	.000	.000	.000	.000	.000
48	.000	.000	.000	.000	.000
49	.000	.000	.000	.000	.000
50	.000	.000	.000	.000	.000
51	.000	.000	.000	.000	.000
52	.000	.000	.000	.000	.000
53	.000	.000	.000	.000	.000
54	.000	.000	.000	.000	.000
55	.000	.000	.000	.000	.000
56	.000	.000	.000	.000	.000
57	.000	.000	.000	.000	.000
58	.000	.000	.000	.000	.000
59	.000	.000	.000	.000	.000
60	.000	.000	.000	.000	.000
61	.000	.000	.000	.000	.000
62	.000	.000	.000	.000	.000
63	.000	.000	.000	.000	.000
64	.000	.000	.000	.000	.000
65	.000	.000	.000	.000	.000
66	.000	.000	.000	.000	.000
67	.000	.000	.000	.000	.000
68	.000	.000	.000	.000	.000
69	.000	.000	.000	.000	.000
70	.000	.000	.000	.000	.000
71	.000	.000	.000	.000	.000
72	.000	.000	.000	.000	.000
73	.000	.000	.000	.000	.000

74	.000	.000	.000	.000	.000
75	.000	.000	.000	.000	.000
76	.000	.000	.000	.000	.000
77	.000	.000	.000	.000	.000
78	.000	.000	.000	.000	.000
79	.000	.000	.000	.000	.000
80	.000	.000	.000	.000	.000
81	.000	.000	.000	.000	.000
82	.000	.000	.000	.000	.000

ESTIMATED COV. MATRIX FOR PARAMETER ESTIMATES

	11	12	13	14	15
11	.078				
12	.039	.078			
13	.039	.039	.078		
14	.040	.039	.040	.082	
15	.039	.039	.040	.041	.078
16	.038	.038	.038	.038	.039
17	.039	.038	.039	.039	.039
18	.039	.039	.039	.038	.039
19	.039	.039	.039	.040	.039
20	.040	.040	.040	.040	.039
21	.039	.038	.039	.039	.040
22	.039	.038	.039	.039	.040
23	.039	.040	.040	.039	.039
24	.039	.039	.039	.039	.039
25	.039	.039	.040	.040	.040
26	.039	.038	.039	.041	.040
27	.039	.039	.039	.040	.039
28	.039	.039	.039	.040	.039
29	.039	.039	.039	.039	.039
30	.039	.039	.039	.039	.039
31	.039	.039	.039	.038	.039
32	.040	.039	.040	.041	.040
33	.040	.040	.040	.041	.040
34	.040	.040	.040	.040	.040
35	.039	.039	.039	.039	.039
36	.039	.039	.039	.040	.039
37	.039	.039	.039	.039	.039
38	.039	.040	.040	.040	.039
39	.040	.039	.040	.041	.040
40	.040	.040	.040	.039	.039
41	.039	.039	.039	.040	.040
42	.039	.039	.039	.039	.039
43	.000	.000	.000	.000	.000
44	.000	.000	.000	.000	.000
45	.000	.000	.000	.000	.000
46	.000	.000	.000	.000	.000
47	.000	.000	.000	.000	.000
48	.000	.000	.000	.000	.000

49	.000	.000	.000	.000	.000
50	.000	.000	.000	.000	.000
51	.000	.000	.000	.000	.000
52	.000	.000	.000	.000	.000
53	.000	.000	.000	.000	.000
54	.000	.000	.000	.000	.000
55	.000	.000	.000	.000	.000
56	.000	.000	.000	.000	.000
57	.000	.000	.000	.000	.000
58	.000	.000	.000	.000	.000
59	.000	.000	.000	.000	.000
60	.000	.000	.000	.000	.000
61	.000	.000	.000	.000	.000
62	.000	.000	.000	.000	.000
63	.000	.000	.000	.000	.000
64	.000	.000	.000	.000	.000
65	.000	.000	.000	.000	.000
66	.000	.000	.000	.000	.000
67	.000	.000	.000	.000	.000
68	.000	.000	.000	.000	.000
69	.000	.000	.000	.000	.000
70	.000	.000	.000	.000	.000
71	.000	.000	.000	.000	.000
72	.000	.000	.000	.000	.000
73	.000	.000	.000	.000	.000
74	.000	.000	.000	.000	.000
75	.000	.000	.000	.000	.000
76	.000	.000	.000	.000	.000
77	.000	.000	.000	.000	.000
78	.000	.000	.000	.000	.000
79	.000	.000	.000	.000	.000
80	.000	.000	.000	.000	.000
81	.000	.000	.000	.000	.000
82	.000	.000	.000	.000	.000

ESTIMATED COV. MATRIX FOR PARAMETER ESTIMATES

	16	17	18	19	20
16	.078				
17	.039	.077			
18	.039	.039	.078		
19	.038	.039	.039	.078	
20	.039	.039	.039	.040	.080
21	.039	.039	.039	.039	.039
22	.039	.039	.040	.039	.039
23	.039	.039	.039	.039	.041
24	.039	.039	.039	.039	.040
25	.039	.039	.039	.039	.040
26	.039	.039	.039	.039	.039
27	.038	.039	.039	.039	.039
28	.039	.039	.039	.039	.039

29	.039	.039	.039	.039	.039
30	.039	.039	.039	.039	.040
31	.039	.039	.039	.039	.040
32	.038	.039	.039	.040	.040
33	.038	.039	.039	.040	.041
34	.038	.039	.039	.040	.041
35	.039	.039	.039	.039	.040
36	.039	.039	.039	.039	.040
37	.038	.039	.039	.039	.039
38	.038	.039	.039	.039	.040
39	.039	.039	.039	.040	.040
40	.038	.038	.039	.039	.041
41	.039	.039	.039	.039	.039
42	.039	.039	.039	.039	.040
43	.000	.000	.000	.000	.000
44	.000	.000	.000	.000	.000
45	.000	.000	.000	.000	.000
46	.000	.000	.000	.000	.000
47	.000	.000	.000	.000	.000
48	.000	.000	.000	.000	.000
49	.000	.000	.000	.000	.000
50	.000	.000	.000	.000	.000
51	.000	.000	.000	.000	.000
52	.000	.000	.000	.000	.000
53	.000	.000	.000	.000	.000
54	.000	.000	.000	.000	.000
55	.000	.000	.000	.000	.000
56	.000	.000	.000	.000	.000
57	.000	.000	.000	.000	.000
58	.000	.000	.000	.000	.000
59	.000	.000	.000	.000	.000
60	.000	.000	.000	.000	.000
61	.000	.000	.000	.000	.000
62	.000	.000	.000	.000	.000
63	.000	.000	.000	.000	.000
64	.000	.000	.000	.000	.000
65	.000	.000	.000	.000	.000
66	.000	.000	.000	.000	.000
67	.000	.000	.000	.000	.000
68	.000	.000	.000	.000	.000
69	.000	.000	.000	.000	.000
70	.000	.000	.000	.000	.000
71	.000	.000	.000	.000	.000
72	.000	.000	.000	.000	.000
73	.000	.000	.000	.000	.000
74	.000	.000	.000	.000	.000
75	.000	.000	.000	.000	.000
76	.000	.000	.000	.000	.000
77	.000	.000	.000	.000	.000
78	.000	.000	.000	.000	.000
79	.000	.000	.000	.000	.000
80	.000	.000	.000	.000	.000

81	.000	.000	.000	.000	.000
82	.000	.000	.000	.000	.000

ESTIMATED COV. MATRIX FOR PARAMETER ESTIMATES

	21	22	23	24	25
21	.078				
22	.040	.079			
23	.039	.039	.079		
24	.039	.040	.039	.078	
25	.039	.040	.040	.040	.078
26	.040	.041	.039	.039	.040
27	.039	.039	.039	.039	.039
28	.039	.039	.039	.039	.039
29	.039	.040	.039	.039	.039
30	.039	.039	.039	.039	.039
31	.039	.039	.039	.039	.039
32	.039	.040	.040	.039	.040
33	.039	.040	.040	.040	.040
34	.039	.039	.040	.040	.040
35	.039	.039	.040	.039	.040
36	.039	.039	.040	.039	.040
37	.038	.038	.039	.039	.039
38	.039	.039	.040	.039	.040
39	.040	.041	.040	.040	.040
40	.038	.039	.040	.040	.040
41	.039	.040	.039	.039	.039
42	.039	.039	.039	.039	.039
43	.000	.000	.000	.000	.000
44	.000	.000	.000	.000	.000
45	.000	.000	.000	.000	.000
46	.000	.000	.000	.000	.000
47	.000	.000	.000	.000	.000
48	.000	.000	.000	.000	.000
49	.000	.000	.000	.000	.000
50	.000	.000	.000	.000	.000
51	.000	.000	.000	.000	.000
52	.000	.000	.000	.000	.000
53	.000	.000	.000	.000	.000
54	.000	.000	.000	.000	.000
55	.000	.000	.000	.000	.000
56	.000	.000	.000	.000	.000
57	.000	.000	.000	.000	.000
58	.000	.000	.000	.000	.000
59	.000	.000	.000	.000	.000
60	.000	.000	.000	.000	.000
61	.000	.000	.000	.000	.000
62	.000	.000	.000	.000	.000
63	.000	.000	.000	.000	.000
64	.000	.000	.000	.000	.000
65	.000	.000	.000	.000	.000

66	.000	.000	.000	.000	.000
67	.000	.000	.000	.000	.000
68	.000	.000	.000	.000	.000
69	.000	.000	.000	.000	.000
70	.000	.000	.000	.000	.000
71	.000	.000	.000	.000	.000
72	.000	.000	.000	.000	.000
73	.000	.000	.000	.000	.000
74	.000	.000	.000	.000	.000
75	.000	.000	.000	.000	.000
76	.000	.000	.000	.000	.000
77	.000	.000	.000	.000	.000
78	.000	.000	.000	.000	.000
79	.000	.000	.000	.000	.000
80	.000	.000	.000	.000	.000
81	.000	.000	.000	.000	.000
82	.000	.000	.000	.000	.000

ESTIMATED COV. MATRIX FOR PARAMETER ESTIMATES

	26	27	28	29	30
26	.080				
27	.039	.078			
28	.039	.039	.078		
29	.040	.039	.039	.078	
30	.039	.039	.039	.039	.078
31	.039	.039	.039	.039	.039
32	.040	.040	.039	.039	.039
33	.040	.040	.040	.040	.040
34	.039	.040	.039	.039	.040
35	.039	.039	.039	.039	.039
36	.039	.039	.039	.039	.039
37	.038	.039	.039	.039	.039
38	.039	.039	.039	.039	.039
39	.041	.039	.040	.040	.040
40	.038	.039	.039	.039	.039
41	.040	.039	.039	.039	.039
42	.039	.039	.039	.039	.039
43	.000	.000	.000	.000	.000
44	.000	.000	.000	.000	.000
45	.000	.000	.000	.000	.000
46	.000	.000	.000	.000	.000
47	.000	.000	.000	.000	.000
48	.000	.000	.000	.000	.000
49	.000	.000	.000	.000	.000
50	.000	.000	.000	.000	.000
51	.000	.000	.000	.000	.000
52	.000	.000	.000	.000	.000
53	.000	.000	.000	.000	.000
54	.000	.000	.000	.000	.000
55	.000	.000	.000	.000	.000

56	.000	.000	.000	.000	.000
57	.000	.000	.000	.000	.000
58	.000	.000	.000	.000	.000
59	.000	.000	.000	.000	.000
60	.000	.000	.000	.000	.000
61	.000	.000	.000	.000	.000
62	.000	.000	.000	.000	.000
63	.000	.000	.000	.000	.000
64	.000	.000	.000	.000	.000
65	.000	.000	.000	.000	.000
66	.000	.000	.000	.000	.000
67	.000	.000	.000	.000	.000
68	.000	.000	.000	.000	.000
69	.000	.000	.000	.000	.000
70	.000	.000	.000	.000	.000
71	.000	.000	.000	.000	.000
72	.000	.000	.000	.000	.000
73	.000	.000	.000	.000	.000
74	.000	.000	.000	.000	.000
75	.000	.000	.000	.000	.000
76	.000	.000	.000	.000	.000
77	.000	.000	.000	.000	.000
78	.000	.000	.000	.000	.000
79	.000	.000	.000	.000	.000
80	.000	.000	.000	.000	.000
81	.000	.000	.000	.000	.000
82	.000	.000	.000	.000	.000

ESTIMATED COV. MATRIX FOR PARAMETER ESTIMATES

	31	32	33	34	35
31	.078				
32	.039	.079			
33	.039	.041	.080		
34	.039	.040	.041	.080	
35	.039	.040	.040	.040	.078
36	.039	.040	.040	.040	.039
37	.039	.039	.039	.039	.039
38	.039	.040	.040	.040	.039
39	.039	.041	.041	.040	.040
40	.040	.040	.040	.041	.040
41	.039	.040	.040	.039	.039
42	.039	.039	.040	.040	.039
43	.000	.000	.000	.000	.000
44	.000	.000	.000	.000	.000
45	.000	.000	.000	.000	.000
46	.000	.000	.000	.000	.000
47	.000	.000	.000	.000	.000
48	.000	.000	.000	.000	.000
49	.000	.000	.000	.000	.000
50	.000	.000	.000	.000	.000

51	.000	.000	.000	.000	.000
52	.000	.000	.000	.000	.000
53	.000	.000	.000	.000	.000
54	.000	.000	.000	.000	.000
55	.000	.000	.000	.000	.000
56	.000	.000	.000	.000	.000
57	.000	.000	.000	.000	.000
58	.000	.000	.000	.000	.000
59	.000	.000	.000	.000	.000
60	.000	.000	.000	.000	.000
61	.000	.000	.000	.000	.000
62	.000	.000	.000	.000	.000
63	.000	.000	.000	.000	.000
64	.000	.000	.000	.000	.000
65	.000	.000	.000	.000	.000
66	.000	.000	.000	.000	.000
67	.000	.000	.000	.000	.000
68	.000	.000	.000	.000	.000
69	.000	.000	.000	.000	.000
70	.000	.000	.000	.000	.000
71	.000	.000	.000	.000	.000
72	.000	.000	.000	.000	.000
73	.000	.000	.000	.000	.000
74	.000	.000	.000	.000	.000
75	.000	.000	.000	.000	.000
76	.000	.000	.000	.000	.000
77	.000	.000	.000	.000	.000
78	.000	.000	.000	.000	.000
79	.000	.000	.000	.000	.000
80	.000	.000	.000	.000	.000
81	.000	.000	.000	.000	.000
82	.000	.000	.000	.000	.000

ESTIMATED COV. MATRIX FOR PARAMETER ESTIMATES

	36	37	38	39	40
36	.078				
37	.039	.077			
38	.040	.039	.078		
39	.040	.039	.040	.080	
40	.040	.039	.040	.040	.080
41	.039	.039	.039	.040	.039
42	.039	.039	.039	.040	.039
43	.000	.000	.000	.000	.000
44	.000	.000	.000	.000	.000
45	.000	.000	.000	.000	.000
46	.000	.000	.000	.000	.000
47	.000	.000	.000	.000	.000
48	.000	.000	.000	.000	.000
49	.000	.000	.000	.000	.000
50	.000	.000	.000	.000	.000

51	.000	.000	.000	.000	.000
52	.000	.000	.000	.000	.000
53	.000	.000	.000	.000	.000
54	.000	.000	.000	.000	.000
55	.000	.000	.000	.000	.000
56	.000	.000	.000	.000	.000
57	.000	.000	.000	.000	.000
58	.000	.000	.000	.000	.000
59	.000	.000	.000	.000	.000
60	.000	.000	.000	.000	.000
61	.000	.000	.000	.000	.000
62	.000	.000	.000	.000	.000
63	.000	.000	.000	.000	.000
64	.000	.000	.000	.000	.000
65	.000	.000	.000	.000	.000
66	.000	.000	.000	.000	.000
67	.000	.000	.000	.000	.000
68	.000	.000	.000	.000	.000
69	.000	.000	.000	.000	.000
70	.000	.000	.000	.000	.000
71	.000	.000	.000	.000	.000
72	.000	.000	.000	.000	.000
73	.000	.000	.000	.000	.000
74	.000	.000	.000	.000	.000
75	.000	.000	.000	.000	.000
76	.000	.000	.000	.000	.000
77	.000	.000	.000	.000	.000
78	.000	.000	.000	.000	.000
79	.000	.000	.000	.000	.000
80	.000	.000	.000	.000	.000
81	.000	.000	.000	.000	.000
82	.000	.000	.000	.000	.000

ESTIMATED COV. MATRIX FOR PARAMETER ESTIMATES

	41	42	43	44	45
41	.078				
42	.039	.078			
43	.000	.000	.000		
44	.000	.000	.000	.065	
45	.000	.000	.000	.033	.066
46	.000	.000	.000	.033	.034
47	.000	.000	.000	.033	.033
48	.000	.000	.000	.033	.033
49	.000	.000	.000	.033	.033
50	.000	.000	.000	.032	.033
51	.000	.000	.000	.033	.033
52	.000	.000	.000	.033	.033
53	.000	.000	.000	.033	.033
54	.000	.000	.000	.032	.033
55	.000	.000	.000	.032	.033

56	.000	.000	.000	.032	.033
57	.000	.000	.000	.033	.033
58	.000	.000	.000	.033	.034
59	.000	.000	.000	.033	.033
60	.000	.000	.000	.033	.033
61	.000	.000	.000	.033	.033
62	.000	.000	.000	.033	.033
63	.000	.000	.000	.033	.033
64	.000	.000	.000	.033	.033
65	.000	.000	.000	.032	.033
66	.000	.000	.000	.033	.033
67	.000	.000	.000	.033	.033
68	.000	.000	.000	.033	.033
69	.000	.000	.000	.032	.033
70	.000	.000	.000	.033	.033
71	.000	.000	.000	.033	.034
72	.000	.000	.000	.033	.033
73	.000	.000	.000	.033	.033
74	.000	.000	.000	.033	.033
75	.000	.000	.000	.032	.032
76	.000	.000	.000	.033	.033
77	.000	.000	.000	.033	.034
78	.000	.000	.000	.033	.033
79	.000	.000	.000	.033	.033
80	.000	.000	.000	.033	.033
81	.000	.000	.000	.000	.000
82	.000	.000	.000	.000	.000

ESTIMATED COV. MATRIX FOR PARAMETER ESTIMATES

	46	47	48	49	50
46	.067				
47	.034	.066			
48	.033	.033	.065		
49	.033	.033	.033	.065	
50	.033	.033	.032	.033	.065
51	.033	.033	.033	.033	.033
52	.033	.033	.033	.033	.033
53	.033	.033	.033	.033	.033
54	.033	.033	.032	.032	.032
55	.033	.033	.032	.032	.032
56	.033	.033	.033	.033	.032
57	.033	.033	.033	.033	.033
58	.034	.034	.033	.033	.033
59	.033	.033	.033	.033	.033
60	.034	.033	.033	.033	.033
61	.033	.033	.033	.033	.033
62	.033	.033	.033	.033	.033
63	.034	.033	.033	.033	.033
64	.034	.033	.033	.033	.033
65	.033	.033	.032	.032	.032

66	.033	.033	.033	.033	.032
67	.033	.033	.033	.033	.033
68	.033	.033	.033	.033	.032
69	.033	.033	.032	.033	.032
70	.034	.033	.033	.033	.033
71	.034	.034	.033	.033	.033
72	.034	.033	.033	.033	.033
73	.033	.033	.033	.033	.033
74	.033	.033	.033	.033	.033
75	.033	.032	.032	.032	.032
76	.033	.033	.033	.033	.033
77	.034	.034	.033	.033	.033
78	.034	.033	.033	.033	.033
79	.033	.033	.033	.033	.033
80	.033	.033	.033	.033	.033
81	.000	.000	.000	.000	.000
82	.000	.000	.000	.000	.000

ESTIMATED COV. MATRIX FOR PARAMETER ESTIMATES

	51	52	53	54	55
51	.065				
52	.033	.065			
53	.033	.033	.065		
54	.032	.032	.032	.064	
55	.032	.032	.032	.032	.064
56	.033	.033	.033	.032	.032
57	.033	.033	.033	.032	.032
58	.033	.033	.033	.033	.033
59	.033	.033	.033	.032	.032
60	.033	.033	.033	.033	.033
61	.033	.033	.033	.032	.032
62	.033	.033	.033	.032	.032
63	.033	.033	.033	.033	.033
64	.033	.033	.033	.033	.032
65	.033	.033	.033	.032	.032
66	.033	.033	.033	.032	.032
67	.033	.033	.033	.032	.032
68	.033	.033	.033	.032	.032
69	.033	.033	.033	.032	.032
70	.033	.033	.033	.033	.033
71	.033	.033	.033	.033	.033
72	.033	.033	.033	.033	.033
73	.033	.033	.033	.032	.032
74	.033	.033	.033	.032	.032
75	.032	.032	.032	.032	.032
76	.033	.033	.033	.032	.032
77	.033	.033	.033	.033	.033
78	.033	.033	.033	.032	.032
79	.033	.033	.033	.032	.032
80	.033	.033	.033	.032	.032

81	.000	.000	.000	.000	.000
82	.000	.000	.000	.000	.000

ESTIMATED COV. MATRIX FOR PARAMETER ESTIMATES

	56	57	58	59	60
56	.065				
57	.033	.065			
58	.033	.033	.066		
59	.033	.033	.033	.065	
60	.033	.033	.034	.033	.066
61	.033	.033	.033	.033	.033
62	.033	.033	.033	.033	.033
63	.033	.033	.034	.033	.033
64	.033	.033	.033	.033	.033
65	.032	.033	.033	.033	.033
66	.033	.033	.033	.033	.033
67	.033	.033	.033	.033	.033
68	.033	.033	.033	.033	.033
69	.032	.033	.033	.033	.033
70	.033	.033	.034	.033	.033
71	.033	.033	.034	.033	.034
72	.033	.033	.034	.033	.033
73	.033	.033	.033	.033	.033
74	.033	.033	.033	.033	.033
75	.032	.032	.032	.032	.032
76	.033	.033	.033	.033	.033
77	.033	.033	.034	.033	.034
78	.033	.033	.033	.033	.033
79	.033	.033	.033	.033	.033
80	.033	.033	.033	.033	.033
81	.000	.000	.000	.000	.000
82	.000	.000	.000	.000	.000

ESTIMATED COV. MATRIX FOR PARAMETER ESTIMATES

	61	62	63	64	65
61	.065				
62	.033	.065			
63	.033	.033	.066		
64	.033	.033	.033	.065	
65	.033	.033	.033	.033	.065
66	.033	.033	.033	.033	.032
67	.033	.033	.033	.033	.033
68	.033	.033	.033	.033	.032
69	.033	.033	.033	.033	.032
70	.033	.033	.033	.033	.033
71	.033	.033	.034	.033	.033
72	.033	.033	.033	.033	.033
73	.033	.033	.033	.033	.033

74	.033	.033	.033	.033	.033
75	.032	.032	.032	.032	.032
76	.033	.033	.033	.033	.033
77	.033	.033	.034	.034	.033
78	.033	.033	.033	.033	.033
79	.033	.033	.033	.033	.033
80	.033	.033	.033	.033	.032
81	.000	.000	.000	.000	.000
82	.000	.000	.000	.000	.000

ESTIMATED COV. MATRIX FOR PARAMETER ESTIMATES

	66	67	68	69	70
66	.065				
67	.033	.065			
68	.033	.033	.065		
69	.032	.033	.032	.065	
70	.033	.033	.033	.033	.066
71	.033	.033	.033	.033	.034
72	.033	.033	.033	.033	.033
73	.033	.033	.033	.033	.033
74	.033	.033	.033	.033	.033
75	.032	.032	.032	.032	.032
76	.033	.033	.033	.033	.033
77	.033	.033	.033	.033	.034
78	.033	.033	.033	.033	.033
79	.033	.033	.033	.033	.033
80	.033	.033	.033	.033	.033
81	.000	.000	.000	.000	.000
82	.000	.000	.000	.000	.000

ESTIMATED COV. MATRIX FOR PARAMETER ESTIMATES

	71	72	73	74	75
71	.066				
72	.034	.066			
73	.033	.033	.065		
74	.033	.033	.033	.065	
75	.033	.032	.032	.032	.064
76	.033	.033	.033	.033	.032
77	.034	.034	.033	.033	.033
78	.033	.033	.033	.033	.032
79	.033	.033	.033	.033	.032
80	.033	.033	.033	.033	.032
81	.000	.000	.000	.000	.000
82	.000	.000	.000	.000	.000

ESTIMATED COV. MATRIX FOR PARAMETER ESTIMATES

	76	77	78	79	80

76	.065				
77	.033	.066			
78	.033	.033	.065		
79	.033	.033	.033	.065	
80	.033	.033	.033	.033	.065
81	.000	.000	.000	.000	.000
82	.000	.000	.000	.000	.000

ESTIMATED COV. MATRIX FOR PARAMETER ESTIMATES

	81	82
81	.009	
82	.000	.006

ESTIMATED CORR. MATRIX FOR PARAMETER ESTIMATES

	1	2	3	4	5
1	1.000				
2	.000	1.000			
3	-.068	.000	1.000		
4	-.149	.000	-.839	1.000	
5	-.202	.000	.000	.075	1.000
6	-.679	.000	.007	.036	.067
7	-.693	.000	-.007	.081	.045
8	-.707	.000	-.007	.106	.062
9	-.692	.000	-.076	.143	.066
10	-.654	.000	-.148	.164	.016
11	-.656	.000	-.022	.056	-.050
12	-.642	.000	.032	.000	-.107
13	-.661	.000	-.052	.092	-.045
14	-.635	.000	-.219	.233	-.045
15	-.676	.000	-.078	.125	.032
16	-.670	.000	.056	-.021	.053
17	-.660	.000	-.020	.039	.026
18	-.675	.000	.024	.019	.037
19	-.660	.000	-.055	.090	-.033
20	-.669	.000	.027	.053	-.100
21	-.683	.000	-.023	.070	.074
22	-.704	.000	-.006	.088	.098
23	-.660	.000	.013	.041	-.085
24	-.680	.000	.025	.038	.002
25	-.681	.000	.000	.070	-.017
26	-.692	.000	-.084	.144	.107
27	-.653	.000	-.046	.069	-.038
28	-.666	.000	-.028	.063	-.003
29	-.676	.000	-.004	.053	.018
30	-.660	.000	-.013	.048	-.033
31	-.662	.000	.052	-.011	-.029
32	-.671	.000	-.094	.148	-.021

33	-.673	.000	-.072	.143	-.056
34	-.658	.000	-.022	.085	-.114
35	-.673	.000	.008	.046	-.021
36	-.663	.000	-.022	.066	-.047
37	-.643	.000	-.005	.017	-.048
38	-.659	.000	-.019	.063	-.067
39	-.691	.000	-.063	.144	.015
40	-.647	.000	.047	.010	-.141
41	-.681	.000	-.026	.077	.042
42	-.660	.000	-.014	.049	-.034
43	.000	-.363	.000	.000	.000
44	.000	-.682	.000	.000	.000
45	.000	-.701	.000	.000	.000
46	.000	-.713	.000	.000	.000
47	.000	-.703	.000	.000	.000
48	.000	-.684	.000	.000	.000
49	.000	-.685	.000	.000	.000
50	.000	-.681	.000	.000	.000
51	.000	-.691	.000	.000	.000
52	.000	-.692	.000	.000	.000
53	.000	-.694	.000	.000	.000
54	.000	-.673	.000	.000	.000
55	.000	-.672	.000	.000	.000
56	.000	-.682	.000	.000	.000
57	.000	-.688	.000	.000	.000
58	.000	-.707	.000	.000	.000
59	.000	-.688	.000	.000	.000
60	.000	-.704	.000	.000	.000
61	.000	-.694	.000	.000	.000
62	.000	-.694	.000	.000	.000
63	.000	-.701	.000	.000	.000
64	.000	-.698	.000	.000	.000
65	.000	-.680	.000	.000	.000
66	.000	-.684	.000	.000	.000
67	.000	-.689	.000	.000	.000
68	.000	-.684	.000	.000	.000
69	.000	-.681	.000	.000	.000
70	.000	-.701	.000	.000	.000
71	.000	-.709	.000	.000	.000
72	.000	-.703	.000	.000	.000
73	.000	-.692	.000	.000	.000
74	.000	-.690	.000	.000	.000
75	.000	-.669	.000	.000	.000
76	.000	-.691	.000	.000	.000
77	.000	-.710	.000	.000	.000
78	.000	-.695	.000	.000	.000
79	.000	-.691	.000	.000	.000
80	.000	-.684	.000	.000	.000
81	.000	.000	.000	.000	.000
82	.000	.000	.000	.000	.000

ESTIMATED CORR. MATRIX FOR PARAMETER ESTIMATES

	6	7	8	9	10
6	1.000				
7	.505	1.000			
8	.505	.513	1.000		
9	.504	.510	.513	1.000	
10	.496	.500	.499	.508	1.000
11	.497	.501	.499	.499	.499
12	.491	.494	.492	.488	.487
13	.497	.503	.502	.503	.504
14	.485	.493	.492	.505	.517
15	.502	.506	.508	.511	.508
16	.502	.500	.499	.496	.487
17	.501	.501	.499	.500	.499
18	.503	.504	.504	.501	.493
19	.498	.502	.502	.504	.504
20	.493	.502	.504	.497	.490
21	.505	.507	.508	.508	.500
22	.506	.511	.515	.512	.498
23	.495	.501	.500	.496	.493
24	.502	.506	.507	.503	.494
25	.501	.507	.509	.505	.498
26	.504	.508	.512	.515	.508
27	.497	.500	.498	.500	.502
28	.501	.503	.503	.503	.501
29	.503	.506	.506	.505	.498
30	.499	.502	.501	.500	.498
31	.499	.500	.498	.494	.488
32	.498	.506	.507	.510	.510
33	.496	.506	.508	.508	.506
34	.491	.500	.501	.498	.496
35	.501	.505	.505	.502	.496
36	.498	.503	.502	.501	.500
37	.496	.496	.493	.493	.495
38	.496	.502	.501	.500	.498
39	.502	.510	.514	.514	.507
40	.487	.494	.493	.486	.483
41	.504	.507	.508	.508	.502
42	.499	.502	.501	.500	.498
43	.000	.000	.000	.000	.000
44	.000	.000	.000	.000	.000
45	.000	.000	.000	.000	.000
46	.000	.000	.000	.000	.000
47	.000	.000	.000	.000	.000
48	.000	.000	.000	.000	.000
49	.000	.000	.000	.000	.000
50	.000	.000	.000	.000	.000
51	.000	.000	.000	.000	.000
52	.000	.000	.000	.000	.000
53	.000	.000	.000	.000	.000
54	.000	.000	.000	.000	.000

55	.000	.000	.000	.000	.000
56	.000	.000	.000	.000	.000
57	.000	.000	.000	.000	.000
58	.000	.000	.000	.000	.000
59	.000	.000	.000	.000	.000
60	.000	.000	.000	.000	.000
61	.000	.000	.000	.000	.000
62	.000	.000	.000	.000	.000
63	.000	.000	.000	.000	.000
64	.000	.000	.000	.000	.000
65	.000	.000	.000	.000	.000
66	.000	.000	.000	.000	.000
67	.000	.000	.000	.000	.000
68	.000	.000	.000	.000	.000
69	.000	.000	.000	.000	.000
70	.000	.000	.000	.000	.000
71	.000	.000	.000	.000	.000
72	.000	.000	.000	.000	.000
73	.000	.000	.000	.000	.000
74	.000	.000	.000	.000	.000
75	.000	.000	.000	.000	.000
76	.000	.000	.000	.000	.000
77	.000	.000	.000	.000	.000
78	.000	.000	.000	.000	.000
79	.000	.000	.000	.000	.000
80	.000	.000	.000	.000	.000
81	.000	.000	.000	.000	.000
82	.000	.000	.000	.000	.000

ESTIMATED CORR. MATRIX FOR PARAMETER ESTIMATES

	11	12	13	14	15
11	1.000				
12	.503	1.000			
13	.505	.502	1.000		
14	.497	.485	.504	1.000	
15	.501	.492	.505	.506	1.000
16	.495	.493	.493	.472	.495
17	.499	.494	.499	.491	.501
18	.499	.495	.498	.483	.500
19	.504	.500	.506	.504	.505
20	.505	.509	.506	.490	.498
21	.498	.489	.499	.492	.505
22	.496	.487	.499	.488	.507
23	.505	.508	.505	.492	.498
24	.502	.500	.502	.487	.502
25	.504	.502	.506	.494	.504
26	.495	.481	.499	.502	.510
27	.504	.501	.505	.501	.502
28	.503	.498	.504	.497	.504
29	.502	.497	.502	.492	.504

30	.504	.502	.504	.495	.502
31	.501	.503	.499	.479	.495
32	.504	.497	.508	.513	.509
33	.506	.501	.510	.511	.508
34	.506	.508	.508	.500	.500
35	.504	.502	.504	.491	.502
36	.505	.503	.506	.498	.503
37	.502	.502	.501	.490	.497
38	.505	.505	.506	.498	.502
39	.503	.495	.507	.506	.510
40	.504	.511	.502	.483	.490
41	.501	.494	.502	.495	.506
42	.504	.502	.504	.495	.502
43	.000	.000	.000	.000	.000
44	.000	.000	.000	.000	.000
45	.000	.000	.000	.000	.000
46	.000	.000	.000	.000	.000
47	.000	.000	.000	.000	.000
48	.000	.000	.000	.000	.000
49	.000	.000	.000	.000	.000
50	.000	.000	.000	.000	.000
51	.000	.000	.000	.000	.000
52	.000	.000	.000	.000	.000
53	.000	.000	.000	.000	.000
54	.000	.000	.000	.000	.000
55	.000	.000	.000	.000	.000
56	.000	.000	.000	.000	.000
57	.000	.000	.000	.000	.000
58	.000	.000	.000	.000	.000
59	.000	.000	.000	.000	.000
60	.000	.000	.000	.000	.000
61	.000	.000	.000	.000	.000
62	.000	.000	.000	.000	.000
63	.000	.000	.000	.000	.000
64	.000	.000	.000	.000	.000
65	.000	.000	.000	.000	.000
66	.000	.000	.000	.000	.000
67	.000	.000	.000	.000	.000
68	.000	.000	.000	.000	.000
69	.000	.000	.000	.000	.000
70	.000	.000	.000	.000	.000
71	.000	.000	.000	.000	.000
72	.000	.000	.000	.000	.000
73	.000	.000	.000	.000	.000
74	.000	.000	.000	.000	.000
75	.000	.000	.000	.000	.000
76	.000	.000	.000	.000	.000
77	.000	.000	.000	.000	.000
78	.000	.000	.000	.000	.000
79	.000	.000	.000	.000	.000
80	.000	.000	.000	.000	.000
81	.000	.000	.000	.000	.000

82	.000	.000	.000	.000	.000

ESTIMATED CORR. MATRIX FOR PARAMETER ESTIMATES

	16	17	18	19	20
16	1.000				
17	.499	1.000			
18	.502	.501	1.000		
19	.494	.500	.499	1.000	
20	.492	.493	.497	.503	1.000
21	.501	.502	.503	.500	.493
22	.501	.500	.504	.499	.496
23	.494	.496	.498	.504	.512
24	.501	.500	.503	.502	.505
25	.498	.500	.502	.505	.509
26	.496	.500	.500	.500	.489
27	.494	.500	.498	.504	.502
28	.498	.501	.501	.504	.501
29	.500	.501	.503	.502	.501
30	.497	.500	.500	.504	.504
31	.500	.498	.501	.499	.504
32	.490	.499	.498	.508	.505
33	.489	.497	.497	.508	.511
34	.488	.494	.495	.506	.515
35	.499	.500	.502	.503	.507
36	.495	.499	.500	.505	.507
37	.496	.499	.498	.501	.500
38	.494	.498	.498	.505	.509
39	.494	.499	.501	.506	.506
40	.489	.490	.493	.500	.515
41	.500	.502	.503	.502	.498
42	.497	.500	.500	.504	.504
43	.000	.000	.000	.000	.000
44	.000	.000	.000	.000	.000
45	.000	.000	.000	.000	.000
46	.000	.000	.000	.000	.000
47	.000	.000	.000	.000	.000
48	.000	.000	.000	.000	.000
49	.000	.000	.000	.000	.000
50	.000	.000	.000	.000	.000
51	.000	.000	.000	.000	.000
52	.000	.000	.000	.000	.000
53	.000	.000	.000	.000	.000
54	.000	.000	.000	.000	.000
55	.000	.000	.000	.000	.000
56	.000	.000	.000	.000	.000
57	.000	.000	.000	.000	.000
58	.000	.000	.000	.000	.000
59	.000	.000	.000	.000	.000
60	.000	.000	.000	.000	.000
61	.000	.000	.000	.000	.000

62	.000	.000	.000	.000	.000
63	.000	.000	.000	.000	.000
64	.000	.000	.000	.000	.000
65	.000	.000	.000	.000	.000
66	.000	.000	.000	.000	.000
67	.000	.000	.000	.000	.000
68	.000	.000	.000	.000	.000
69	.000	.000	.000	.000	.000
70	.000	.000	.000	.000	.000
71	.000	.000	.000	.000	.000
72	.000	.000	.000	.000	.000
73	.000	.000	.000	.000	.000
74	.000	.000	.000	.000	.000
75	.000	.000	.000	.000	.000
76	.000	.000	.000	.000	.000
77	.000	.000	.000	.000	.000
78	.000	.000	.000	.000	.000
79	.000	.000	.000	.000	.000
80	.000	.000	.000	.000	.000
81	.000	.000	.000	.000	.000
82	.000	.000	.000	.000	.000

ESTIMATED CORR. MATRIX FOR PARAMETER ESTIMATES

	21	22	23	24	25
21	1.000				
22	.509	1.000			
23	.495	.495	1.000		
24	.502	.505	.504	1.000	
25	.502	.505	.506	.507	1.000
26	.509	.512	.490	.500	.501
27	.498	.496	.503	.501	.503
28	.502	.501	.502	.503	.504
29	.504	.505	.501	.504	.505
30	.499	.498	.504	.503	.504
31	.497	.497	.503	.503	.503
32	.502	.503	.503	.502	.507
33	.499	.502	.508	.504	.509
34	.492	.493	.511	.503	.508
35	.501	.502	.505	.505	.507
36	.499	.498	.506	.504	.506
37	.495	.491	.502	.499	.500
38	.497	.496	.508	.503	.506
39	.505	.510	.503	.505	.509
40	.486	.485	.511	.501	.504
41	.506	.507	.499	.504	.505
42	.499	.498	.504	.503	.504
43	.000	.000	.000	.000	.000

44	.000	.000	.000	.000	.000
45	.000	.000	.000	.000	.000
46	.000	.000	.000	.000	.000
47	.000	.000	.000	.000	.000
48	.000	.000	.000	.000	.000
49	.000	.000	.000	.000	.000
50	.000	.000	.000	.000	.000
51	.000	.000	.000	.000	.000
52	.000	.000	.000	.000	.000
53	.000	.000	.000	.000	.000
54	.000	.000	.000	.000	.000
55	.000	.000	.000	.000	.000
56	.000	.000	.000	.000	.000
57	.000	.000	.000	.000	.000
58	.000	.000	.000	.000	.000
59	.000	.000	.000	.000	.000
60	.000	.000	.000	.000	.000
61	.000	.000	.000	.000	.000
62	.000	.000	.000	.000	.000
63	.000	.000	.000	.000	.000
64	.000	.000	.000	.000	.000
65	.000	.000	.000	.000	.000
66	.000	.000	.000	.000	.000
67	.000	.000	.000	.000	.000
68	.000	.000	.000	.000	.000
69	.000	.000	.000	.000	.000
70	.000	.000	.000	.000	.000
71	.000	.000	.000	.000	.000
72	.000	.000	.000	.000	.000
73	.000	.000	.000	.000	.000
74	.000	.000	.000	.000	.000
75	.000	.000	.000	.000	.000
76	.000	.000	.000	.000	.000
77	.000	.000	.000	.000	.000
78	.000	.000	.000	.000	.000
79	.000	.000	.000	.000	.000
80	.000	.000	.000	.000	.000
81	.000	.000	.000	.000	.000
82	.000	.000	.000	.000	.000

ESTIMATED CORR. MATRIX FOR PARAMETER ESTIMATES

	26	27	28	29	30
26	1.000				
27	.497	1.000			
28	.501	.503	1.000		
29	.503	.501	.503	1.000	
30	.496	.503	.503	.502	1.000
31	.490	.499	.500	.501	.501
32	.507	.505	.504	.503	.503
33	.503	.505	.504	.503	.504

34	.490	.504	.501	.500	.504
35	.498	.502	.503	.504	.504
36	.497	.504	.503	.503	.504
37	.490	.501	.500	.499	.501
38	.494	.504	.503	.502	.504
39	.511	.503	.504	.505	.503
40	.477	.500	.497	.496	.502
41	.507	.501	.503	.504	.501
42	.497	.503	.503	.502	.503
43	.000	.000	.000	.000	.000
44	.000	.000	.000	.000	.000
45	.000	.000	.000	.000	.000
46	.000	.000	.000	.000	.000
47	.000	.000	.000	.000	.000
48	.000	.000	.000	.000	.000
49	.000	.000	.000	.000	.000
50	.000	.000	.000	.000	.000
51	.000	.000	.000	.000	.000
52	.000	.000	.000	.000	.000
53	.000	.000	.000	.000	.000
54	.000	.000	.000	.000	.000
55	.000	.000	.000	.000	.000
56	.000	.000	.000	.000	.000
57	.000	.000	.000	.000	.000
58	.000	.000	.000	.000	.000
59	.000	.000	.000	.000	.000
60	.000	.000	.000	.000	.000
61	.000	.000	.000	.000	.000
62	.000	.000	.000	.000	.000
63	.000	.000	.000	.000	.000
64	.000	.000	.000	.000	.000
65	.000	.000	.000	.000	.000
66	.000	.000	.000	.000	.000
67	.000	.000	.000	.000	.000
68	.000	.000	.000	.000	.000
69	.000	.000	.000	.000	.000
70	.000	.000	.000	.000	.000
71	.000	.000	.000	.000	.000
72	.000	.000	.000	.000	.000
73	.000	.000	.000	.000	.000
74	.000	.000	.000	.000	.000
75	.000	.000	.000	.000	.000
76	.000	.000	.000	.000	.000
77	.000	.000	.000	.000	.000
78	.000	.000	.000	.000	.000
79	.000	.000	.000	.000	.000
80	.000	.000	.000	.000	.000
81	.000	.000	.000	.000	.000
82	.000	.000	.000	.000	.000

ESTIMATED CORR. MATRIX FOR PARAMETER ESTIMATES

	31	32	33	34	35
31	1.000				
32	.496	1.000			
33	.498	.514	1.000		
34	.501	.508	.514	1.000	
35	.503	.504	.506	.505	1.000
36	.501	.506	.508	.508	.505
37	.500	.498	.498	.501	.500
38	.502	.506	.509	.510	.505
39	.497	.513	.514	.507	.505
40	.503	.498	.505	.514	.503
41	.499	.505	.503	.498	.503
42	.501	.503	.505	.505	.504
43	.000	.000	.000	.000	.000
44	.000	.000	.000	.000	.000
45	.000	.000	.000	.000	.000
46	.000	.000	.000	.000	.000
47	.000	.000	.000	.000	.000
48	.000	.000	.000	.000	.000
49	.000	.000	.000	.000	.000
50	.000	.000	.000	.000	.000
51	.000	.000	.000	.000	.000
52	.000	.000	.000	.000	.000
53	.000	.000	.000	.000	.000
54	.000	.000	.000	.000	.000
55	.000	.000	.000	.000	.000
56	.000	.000	.000	.000	.000
57	.000	.000	.000	.000	.000
58	.000	.000	.000	.000	.000
59	.000	.000	.000	.000	.000
60	.000	.000	.000	.000	.000
61	.000	.000	.000	.000	.000
62	.000	.000	.000	.000	.000
63	.000	.000	.000	.000	.000
64	.000	.000	.000	.000	.000
65	.000	.000	.000	.000	.000
66	.000	.000	.000	.000	.000
67	.000	.000	.000	.000	.000
68	.000	.000	.000	.000	.000
69	.000	.000	.000	.000	.000
70	.000	.000	.000	.000	.000
71	.000	.000	.000	.000	.000
72	.000	.000	.000	.000	.000
73	.000	.000	.000	.000	.000
74	.000	.000	.000	.000	.000
75	.000	.000	.000	.000	.000
76	.000	.000	.000	.000	.000
77	.000	.000	.000	.000	.000
78	.000	.000	.000	.000	.000
79	.000	.000	.000	.000	.000
80	.000	.000	.000	.000	.000

81	.000	.000	.000	.000	.000
82	.000	.000	.000	.000	.000

ESTIMATED CORR. MATRIX FOR PARAMETER ESTIMATES

	36	37	38	39	40
36	1.000				
37	.501	1.000			
38	.506	.502	1.000		
39	.505	.496	.505	1.000	
40	.505	.500	.507	.497	1.000
41	.502	.497	.501	.507	.492
42	.504	.501	.505	.503	.502
43	.000	.000	.000	.000	.000
44	.000	.000	.000	.000	.000
45	.000	.000	.000	.000	.000
46	.000	.000	.000	.000	.000
47	.000	.000	.000	.000	.000
48	.000	.000	.000	.000	.000
49	.000	.000	.000	.000	.000
50	.000	.000	.000	.000	.000
51	.000	.000	.000	.000	.000
52	.000	.000	.000	.000	.000
53	.000	.000	.000	.000	.000
54	.000	.000	.000	.000	.000
55	.000	.000	.000	.000	.000
56	.000	.000	.000	.000	.000
57	.000	.000	.000	.000	.000
58	.000	.000	.000	.000	.000
59	.000	.000	.000	.000	.000
60	.000	.000	.000	.000	.000
61	.000	.000	.000	.000	.000
62	.000	.000	.000	.000	.000
63	.000	.000	.000	.000	.000
64	.000	.000	.000	.000	.000
65	.000	.000	.000	.000	.000
66	.000	.000	.000	.000	.000
67	.000	.000	.000	.000	.000
68	.000	.000	.000	.000	.000
69	.000	.000	.000	.000	.000
70	.000	.000	.000	.000	.000
71	.000	.000	.000	.000	.000
72	.000	.000	.000	.000	.000
73	.000	.000	.000	.000	.000
74	.000	.000	.000	.000	.000
75	.000	.000	.000	.000	.000
76	.000	.000	.000	.000	.000
77	.000	.000	.000	.000	.000
78	.000	.000	.000	.000	.000
79	.000	.000	.000	.000	.000
80	.000	.000	.000	.000	.000

81	.000	.000	.000	.000	.000
82	.000	.000	.000	.000	.000

ESTIMATED CORR. MATRIX FOR PARAMETER ESTIMATES

	41	42	43	44	45
41	1.000				
42	.501	1.000			
43	.000	.000	1.000		
44	.000	.000	.068	1.000	
45	.000	.000	.132	.503	1.000
46	.000	.000	.179	.503	.511
47	.000	.000	.139	.503	.509
48	.000	.000	.072	.502	.504
49	.000	.000	.076	.503	.504
50	.000	.000	.065	.502	.503
51	.000	.000	.096	.503	.506
52	.000	.000	.100	.503	.506
53	.000	.000	.106	.503	.507
54	.000	.000	.040	.501	.501
55	.000	.000	.038	.501	.500
56	.000	.000	.067	.502	.503
57	.000	.000	.085	.503	.505
58	.000	.000	.156	.503	.510
59	.000	.000	.085	.503	.505
60	.000	.000	.141	.503	.509
61	.000	.000	.108	.503	.507
62	.000	.000	.109	.503	.507
63	.000	.000	.131	.503	.509
64	.000	.000	.122	.503	.508
65	.000	.000	.062	.502	.503
66	.000	.000	.074	.502	.504
67	.000	.000	.090	.503	.505
68	.000	.000	.074	.502	.504
69	.000	.000	.064	.502	.503
70	.000	.000	.131	.503	.509
71	.000	.000	.162	.503	.510
72	.000	.000	.140	.503	.509
73	.000	.000	.101	.503	.506
74	.000	.000	.095	.503	.506
75	.000	.000	.030	.501	.499
76	.000	.000	.098	.503	.506
77	.000	.000	.167	.503	.511
78	.000	.000	.112	.503	.507
79	.000	.000	.096	.503	.506
80	.000	.000	.075	.503	.504
81	.000	.000	.000	.000	.000
82	.000	.000	.000	.000	.000

ESTIMATED CORR. MATRIX FOR PARAMETER ESTIMATES

	46	47	48	49	50
46	1.000				
47	.512	1.000			
48	.504	.504	1.000		
49	.504	.504	.503	1.000	
50	.503	.503	.502	.502	1.000
51	.507	.506	.503	.504	.503
52	.507	.507	.503	.504	.503
53	.508	.507	.504	.504	.503
54	.499	.500	.501	.501	.501
55	.498	.500	.501	.501	.501
56	.503	.503	.502	.503	.502
57	.505	.505	.503	.503	.503
58	.514	.511	.504	.504	.503
59	.505	.505	.503	.503	.503
60	.512	.510	.504	.504	.503
61	.508	.507	.504	.504	.503
62	.508	.507	.504	.504	.503
63	.511	.509	.504	.504	.503
64	.510	.508	.504	.504	.503
65	.502	.503	.502	.502	.502
66	.504	.504	.503	.503	.502
67	.506	.506	.503	.503	.503
68	.504	.504	.503	.503	.502
69	.502	.503	.502	.502	.502
70	.511	.509	.504	.504	.503
71	.514	.511	.504	.504	.503
72	.512	.510	.504	.504	.503
73	.507	.507	.503	.504	.503
74	.507	.506	.503	.504	.503
75	.497	.499	.501	.501	.501
76	.507	.506	.503	.504	.503
77	.515	.511	.504	.504	.503
78	.509	.508	.504	.504	.503
79	.507	.506	.503	.504	.503
80	.504	.504	.503	.503	.502
81	.000	.000	.000	.000	.000
82	.000	.000	.000	.000	.000

ESTIMATED CORR. MATRIX FOR PARAMETER ESTIMATES

	51	52	53	54	55
51	1.000				
52	.505	1.000			
53	.505	.505	1.000		
54	.501	.501	.501	1.000	
55	.501	.501	.501	.501	1.000
56	.503	.503	.503	.501	.501
57	.504	.504	.504	.501	.501
58	.507	.507	.508	.500	.499

59	.504	.504	.504	.501	.501
60	.506	.507	.507	.500	.500
61	.505	.505	.506	.501	.501
62	.505	.505	.506	.501	.501
63	.506	.506	.507	.501	.500
64	.506	.506	.506	.501	.501
65	.503	.503	.503	.501	.501
66	.503	.504	.504	.501	.501
67	.504	.504	.505	.501	.501
68	.503	.504	.504	.501	.501
69	.503	.503	.503	.501	.501
70	.506	.506	.507	.501	.500
71	.507	.507	.508	.500	.499
72	.506	.507	.507	.500	.500
73	.505	.505	.505	.501	.501
74	.505	.505	.505	.501	.501
75	.500	.500	.500	.501	.501
76	.505	.505	.505	.501	.501
77	.507	.507	.508	.499	.499
78	.505	.506	.506	.501	.501
79	.505	.505	.505	.501	.501
80	.504	.504	.504	.501	.501
81	.000	.000	.000	.000	.000
82	.000	.000	.000	.000	.000

ESTIMATED CORR. MATRIX FOR PARAMETER ESTIMATES

	56	57	58	59	60
56	1.000				
57	.503	1.000			
58	.503	.505	1.000		
59	.503	.504	.505	1.000	
60	.503	.505	.511	.505	1.000
61	.503	.504	.508	.504	.507
62	.503	.504	.508	.504	.507
63	.503	.505	.510	.505	.509
64	.503	.505	.509	.505	.509
65	.502	.502	.503	.502	.503
66	.502	.503	.504	.503	.504
67	.503	.504	.506	.504	.506
68	.502	.503	.504	.503	.504
69	.502	.503	.503	.503	.503
70	.503	.505	.510	.505	.509
71	.503	.505	.513	.505	.511
72	.503	.505	.511	.505	.510
73	.503	.504	.507	.504	.507
74	.503	.504	.506	.504	.506
75	.501	.500	.498	.500	.499
76	.503	.504	.507	.504	.506
77	.503	.505	.513	.505	.512
78	.503	.505	.508	.505	.508

79	.503	.504	.507	.504	.506
80	.503	.503	.504	.503	.504
81	.000	.000	.000	.000	.000
82	.000	.000	.000	.000	.000

ESTIMATED CORR. MATRIX FOR PARAMETER ESTIMATES

	61	62	63	64	65
61	1.000				
62	.506	1.000			
63	.507	.507	1.000		
64	.507	.507	.508	1.000	
65	.503	.503	.503	.503	1.000
66	.504	.504	.504	.504	.502
67	.505	.505	.505	.505	.503
68	.504	.504	.504	.504	.502
69	.503	.503	.503	.503	.502
70	.507	.507	.509	.508	.503
71	.508	.508	.510	.509	.502
72	.507	.507	.509	.508	.503
73	.505	.505	.506	.506	.503
74	.505	.505	.506	.506	.503
75	.500	.500	.499	.500	.501
76	.505	.505	.506	.506	.503
77	.508	.508	.511	.510	.502
78	.506	.506	.507	.507	.503
79	.505	.505	.506	.506	.503
80	.504	.504	.504	.504	.502
81	.000	.000	.000	.000	.000
82	.000	.000	.000	.000	.000

ESTIMATED CORR. MATRIX FOR PARAMETER ESTIMATES

	66	67	68	69	70
66	1.000				
67	.503	1.000			
68	.503	.503	1.000		
69	.502	.503	.502	1.000	
70	.504	.505	.504	.503	1.000
71	.504	.506	.504	.503	.510
72	.504	.506	.504	.503	.509
73	.504	.504	.504	.503	.506
74	.503	.504	.503	.503	.506
75	.501	.500	.501	.501	.499
76	.503	.504	.503	.503	.506
77	.504	.506	.504	.503	.511
78	.504	.505	.504	.503	.507
79	.503	.504	.503	.503	.506
80	.503	.503	.503	.502	.504
81	.000	.000	.000	.000	.000

82	.000	.000	.000	.000	.000

ESTIMATED CORR. MATRIX FOR PARAMETER ESTIMATES

	71	72	73	74	75
71	1.000				
72	.511	1.000			
73	.507	.507	1.000		
74	.507	.506	.505	1.000	
75	.498	.499	.500	.500	1.000
76	.507	.506	.505	.505	.500
77	.513	.512	.507	.507	.498
78	.508	.508	.506	.505	.500
79	.507	.506	.505	.505	.500
80	.504	.504	.504	.503	.501
81	.000	.000	.000	.000	.000
82	.000	.000	.000	.000	.000

ESTIMATED CORR. MATRIX FOR PARAMETER ESTIMATES

	76	77	78	79	80
76	1.000				
77	.507	1.000			
78	.505	.509	1.000		
79	.505	.507	.505	1.000	
80	.504	.504	.504	.503	1.000
81	.000	.000	.000	.000	.000
82	.000	.000	.000	.000	.000

ESTIMATED CORR. MATRIX FOR PARAMETER ESTIMATES

	81	82
81	1.000	
82	.000	1.000

TECHNICAL 4 OUTPUT

ESTIMATES DERIVED FROM THE MODEL

ESTIMATED COVARIANCE MATRIX FOR THE LATENT VARIABLES

	IC	LEG	WICH	SCHW	P2DUMMY
IC	11.415				

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Simultanes Mehrgleichungsmodell fuer die Beziehung

LEG	-8.044	13.812			

WICH	-6.186	10.948	12.744		
SCHW	2.100	-1.153	-1.179	6.805	
P2DUMMY	-.032	.006	.023	-.043	.026
P3DUMMY	.074	-.032	-.028	-.026	-.001
P4DUMMY	.056	-.065	-.065	-.032	-.001
P5DUMMY	-.075	-.007	-.033	-.038	-.001
P6DUMMY	-.021	.071	.019	-.016	-.001
P8DUMMY	.007	.013	.016	.020	-.001
P9DUMMY	.050	-.003	.025	.049	-.001
P10DUMMY	-.024	.013	.001	.018	-.001
P11DUMMY	-.053	.086	-.002	.020	-.001
P12DUMMY	.014	.017	-.007	-.021	-.001
P13DUMMY	.043	.004	.045	-.038	-.001
P14DUMMY	-.034	.038	.046	-.023	-.001
P15DUMMY	-.040	-.001	.023	-.027	-.001
P16DUMMY	-.040	.021	.009	.011	-.001
P17DUMMY	.067	-.063	-.046	.053	-.001
P18DUMMY	-.076	.007	.009	-.046	-.001
P19DUMMY	-.077	-.039	-.035	-.054	-.001
P20DUMMY	.044	-.024	-.009	.041	-.001
P21DUMMY	.023	-.030	-.009	-.006	-.001
P22DUMMY	.030	-.034	-.027	.006	-.001
P23DUMMY	-.039	.009	-.020	-.061	-.001
P24DUMMY	-.010	.033	.028	.012	-.001
P25DUMMY	.036	.017	.018	-.006	-.001
P26DUMMY	-.021	-.004	.006	-.015	-.001
P27DUMMY	.024	.011	.018	.010	-.001
P28DUMMY	-.004	-.011	.026	.008	-.001
P29DUMMY	.021	.007	-.027	.009	-.001
P30DUMMY	-.085	-.024	-.051	.030	-.001
P31DUMMY	.043	-.031	-.034	.059	-.001
P32DUMMY	-.020	-.017	-.003	.006	-.001
P33DUMMY	-.011	.001	.002	.020	-.001
P34DUMMY	-.043	.037	.053	.015	-.001
P35DUMMY	-.002	-.003	.000	.030	-.001
P36DUMMY	.039	-.031	-.055	-.008	-.001
P37DUMMY	.090	-.042	-.012	.071	-.001
P38DUMMY	.041	.002	.001	-.027	-.001
P39DUMMY	.028	.010	.017	.011	-.001

ESTIMATED COVARIANCE MATRIX FOR THE LATENT VARIABLES

	P3DUMMY	P4DUMMY	P5DUMMY	P6DUMMY	P8DUMMY
P3DUMMY	.026				
P4DUMMY	-.001	.026			
P5DUMMY	-.001	-.001	.026		
P6DUMMY	-.001	-.001	-.001	.026	
P8DUMMY	-.001	-.001	-.001	-.001	.026
P9DUMMY	-.001	-.001	-.001	-.001	-.001
P10DUMMY	-.001	-.001	-.001	-.001	-.001
P11DUMMY	-.001	-.001	-.001	-.001	-.001

P12DUMMY	-.001	-.001	-.001	-.001	-.001
P13DUMMY	-.001	-.001	-.001	-.001	-.001
P14DUMMY	-.001	-.001	-.001	-.001	-.001
P15DUMMY	-.001	-.001	-.001	-.001	-.001
P16DUMMY	-.001	-.001	-.001	-.001	-.001
P17DUMMY	-.001	-.001	-.001	-.001	-.001
P18DUMMY	-.001	-.001	-.001	-.001	-.001
P19DUMMY	-.001	-.001	-.001	-.001	-.001
P20DUMMY	-.001	-.001	-.001	-.001	-.001
P21DUMMY	-.001	-.001	-.001	-.001	-.001
P22DUMMY	-.001	-.001	-.001	-.001	-.001
P23DUMMY	-.001	-.001	-.001	-.001	-.001
P24DUMMY	-.001	-.001	-.001	-.001	-.001
P25DUMMY	-.001	-.001	-.001	-.001	-.001
P26DUMMY	-.001	-.001	-.001	-.001	-.001
P27DUMMY	-.001	-.001	-.001	-.001	-.001
P28DUMMY	-.001	-.001	-.001	-.001	-.001
P29DUMMY	-.001	-.001	-.001	-.001	-.001
P30DUMMY	-.001	-.001	-.001	-.001	-.001
P31DUMMY	-.001	-.001	-.001	-.001	-.001
P32DUMMY	-.001	-.001	-.001	-.001	-.001
P33DUMMY	-.001	-.001	-.001	-.001	-.001
P34DUMMY	-.001	-.001	-.001	-.001	-.001
P35DUMMY	-.001	-.001	-.001	-.001	-.001
P36DUMMY	-.001	-.001	-.001	-.001	-.001
P37DUMMY	-.001	-.001	-.001	-.001	-.001
P38DUMMY	-.001	-.001	-.001	-.001	-.001
P39DUMMY	-.001	-.001	-.001	-.001	-.001

ESTIMATED COVARIANCE MATRIX FOR THE LATENT VARIABLES

	P9DUMMY	P10DUMMY	P11DUMMY	P12DUMMY	P13DUMMY
P9DUMMY	.026				
P10DUMMY	-.001	.026			
P11DUMMY	-.001	-.001	.026		
P12DUMMY	-.001	-.001	-.001	.026	
P13DUMMY	-.001	-.001	-.001	-.001	.026
P14DUMMY	-.001	-.001	-.001	-.001	-.001
P15DUMMY	-.001	-.001	-.001	-.001	-.001
P16DUMMY	-.001	-.001	-.001	-.001	-.001
P17DUMMY	-.001	-.001	-.001	-.001	-.001
P18DUMMY	-.001	-.001	-.001	-.001	-.001
P19DUMMY	-.001	-.001	-.001	-.001	-.001
P20DUMMY	-.001	-.001	-.001	-.001	-.001
P21DUMMY	-.001	-.001	-.001	-.001	-.001
P22DUMMY	-.001	-.001	-.001	-.001	-.001
P23DUMMY	-.001	-.001	-.001	-.001	-.001
P24DUMMY	-.001	-.001	-.001	-.001	-.001
P25DUMMY	-.001	-.001	-.001	-.001	-.001
P26DUMMY	-.001	-.001	-.001	-.001	-.001
P27DUMMY	-.001	-.001	-.001	-.001	-.001

P28DUMMY	-.001	-.001	-.001	-.001	-.001
P29DUMMY	-.001	-.001	-.001	-.001	-.001
P30DUMMY	-.001	-.001	-.001	-.001	-.001
P31DUMMY	-.001	-.001	-.001	-.001	-.001
P32DUMMY	-.001	-.001	-.001	-.001	-.001
P33DUMMY	-.001	-.001	-.001	-.001	-.001
P34DUMMY	-.001	-.001	-.001	-.001	-.001
P35DUMMY	-.001	-.001	-.001	-.001	-.001
P36DUMMY	-.001	-.001	-.001	-.001	-.001
P37DUMMY	-.001	-.001	-.001	-.001	-.001
P38DUMMY	-.001	-.001	-.001	-.001	-.001
P39DUMMY	-.001	-.001	-.001	-.001	-.001

ESTIMATED COVARIANCE MATRIX FOR THE LATENT VARIABLES

	P14DUMMY	P15DUMMY	P16DUMMY	P17DUMMY	P18DUMMY
P14DUMMY	.026				
P15DUMMY	-.001	.026			
P16DUMMY	-.001	-.001	.026		
P17DUMMY	-.001	-.001	-.001	.026	
P18DUMMY	-.001	-.001	-.001	-.001	.026
P19DUMMY	-.001	-.001	-.001	-.001	-.001
P20DUMMY	-.001	-.001	-.001	-.001	-.001
P21DUMMY	-.001	-.001	-.001	-.001	-.001
P22DUMMY	-.001	-.001	-.001	-.001	-.001
P23DUMMY	-.001	-.001	-.001	-.001	-.001
P24DUMMY	-.001	-.001	-.001	-.001	-.001
P25DUMMY	-.001	-.001	-.001	-.001	-.001
P26DUMMY	-.001	-.001	-.001	-.001	-.001
P27DUMMY	-.001	-.001	-.001	-.001	-.001
P28DUMMY	-.001	-.001	-.001	-.001	-.001
P29DUMMY	-.001	-.001	-.001	-.001	-.001
P30DUMMY	-.001	-.001	-.001	-.001	-.001
P31DUMMY	-.001	-.001	-.001	-.001	-.001
P32DUMMY	-.001	-.001	-.001	-.001	-.001
P33DUMMY	-.001	-.001	-.001	-.001	-.001
P34DUMMY	-.001	-.001	-.001	-.001	-.001
P35DUMMY	-.001	-.001	-.001	-.001	-.001
P36DUMMY	-.001	-.001	-.001	-.001	-.001
P37DUMMY	-.001	-.001	-.001	-.001	-.001
P38DUMMY	-.001	-.001	-.001	-.001	-.001
P39DUMMY	-.001	-.001	-.001	-.001	-.001

ESTIMATED COVARIANCE MATRIX FOR THE LATENT VARIABLES

	P19DUMMY	P20DUMMY	P21DUMMY	P22DUMMY	P23DUMMY
P19DUMMY	.026				
P20DUMMY	-.001	.026			
P21DUMMY	-.001	-.001	.026		
P22DUMMY	-.001	-.001	-.001	.026	

P23DUMMY	-.001	-.001	-.001	-.001	.026
P24DUMMY	-.001	-.001	-.001	-.001	-.001
P25DUMMY	-.001	-.001	-.001	-.001	-.001
P26DUMMY	-.001	-.001	-.001	-.001	-.001
P27DUMMY	-.001	-.001	-.001	-.001	-.001
P28DUMMY	-.001	-.001	-.001	-.001	-.001
P29DUMMY	-.001	-.001	-.001	-.001	-.001
P30DUMMY	-.001	-.001	-.001	-.001	-.001
P31DUMMY	-.001	-.001	-.001	-.001	-.001
P32DUMMY	-.001	-.001	-.001	-.001	-.001
P33DUMMY	-.001	-.001	-.001	-.001	-.001
P34DUMMY	-.001	-.001	-.001	-.001	-.001
P35DUMMY	-.001	-.001	-.001	-.001	-.001
P36DUMMY	-.001	-.001	-.001	-.001	-.001
P37DUMMY	-.001	-.001	-.001	-.001	-.001
P38DUMMY	-.001	-.001	-.001	-.001	-.001
P39DUMMY	-.001	-.001	-.001	-.001	-.001

ESTIMATED COVARIANCE MATRIX FOR THE LATENT VARIABLES

	P24DUMMY	P25DUMMY	P26DUMMY	P27DUMMY	P28DUMMY
P24DUMMY	.026				
P25DUMMY	-.001	.026			
P26DUMMY	-.001	-.001	.026		
P27DUMMY	-.001	-.001	-.001	.026	
P28DUMMY	-.001	-.001	-.001	-.001	.026
P29DUMMY	-.001	-.001	-.001	-.001	-.001
P30DUMMY	-.001	-.001	-.001	-.001	-.001
P31DUMMY	-.001	-.001	-.001	-.001	-.001
P32DUMMY	-.001	-.001	-.001	-.001	-.001
P33DUMMY	-.001	-.001	-.001	-.001	-.001
P34DUMMY	-.001	-.001	-.001	-.001	-.001
P35DUMMY	-.001	-.001	-.001	-.001	-.001
P36DUMMY	-.001	-.001	-.001	-.001	-.001
P37DUMMY	-.001	-.001	-.001	-.001	-.001
P38DUMMY	-.001	-.001	-.001	-.001	-.001
P39DUMMY	-.001	-.001	-.001	-.001	-.001

ESTIMATED COVARIANCE MATRIX FOR THE LATENT VARIABLES

	P29DUMMY	P30DUMMY	P31DUMMY	P32DUMMY	P33DUMMY
P29DUMMY	.026				
P30DUMMY	-.001	.026			
P31DUMMY	-.001	-.001	.026		
P32DUMMY	-.001	-.001	-.001	.026	
P33DUMMY	-.001	-.001	-.001	-.001	.026
P34DUMMY	-.001	-.001	-.001	-.001	-.001
P35DUMMY	-.001	-.001	-.001	-.001	-.001
P36DUMMY	-.001	-.001	-.001	-.001	-.001
P37DUMMY	-.001	-.001	-.001	-.001	-.001

```
 P38DUMMY       -.001          -.001          -.001          -.001          -.001
 P39DUMMY       -.001          -.001          -.001          -.001          -.001


           ESTIMATED COVARIANCE MATRIX FOR THE LATENT VARIABLES
              P34DUMMY       P35DUMMY       P36DUMMY       P37DUMMY       P38DUMMY
              ________       ________       ________       ________       ________
 P34DUMMY         .026
 P35DUMMY       -.001           .026
 P36DUMMY       -.001          -.001           .026
 P37DUMMY       -.001          -.001          -.001           .026
 P38DUMMY       -.001          -.001          -.001          -.001           .026
 P39DUMMY       -.001          -.001          -.001          -.001          -.001


           ESTIMATED COVARIANCE MATRIX FOR THE LATENT VARIABLES
              P39DUMMY
              ________
 P39DUMMY         .026
Mplus VERSION 1.04                                                     PAGE   38
Simultanes Mehrgleichungsmodell fuer die Beziehung



     Beginning Time:  14:06:08
        Ending Time:  14:06:14
       Elapsed Time:  00:00:06



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C3b: Group A (peip & u questions)

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Mplus VERSION 1.04
MUTHEN & MUTHEN
02/02/2001   3:45 PM

INPUT INSTRUCTIONS

  TITLE: Simultanes Mehrgleichungsmodell fuer die Beziehung
  zwischen IC, LEG, WICH und SCHW (mit WICH --> LEG)

  Stichprobe: Fragen U + PEIP, disaggregrierte Daten

  DATA: FILE IS dummy_pers.dat;

  VARIABLE: NAMES ARE

  LEG SCHW WICH IC
  P1DUMMY P2DUMMY P3DUMMY P4DUMMY P5DUMMY P6DUMMY P8DUMMY P9DUMMY P10DUMMY
  P11DUMMY P12DUMMY P13DUMMY P14DUMMY P15DUMMY P16DUMMY P17DUMMY P18DUMMY
  P19DUMMY P20DUMMY P21DUMMY P22DUMMY P23DUMMY P24DUMMY        P25DUMMY P26DUMMY
  P27DUMMY P28DUMMY P29DUMMY P30DUMMY P31DUMMY P32DUMMY P33DUMMY P34DUMMY
  P35DUMMY P36DUMMY P37DUMMY P38DUMMY P39DUMMY;

  USEVARIABLES IC LEG WICH SCHW
  P2DUMMY P3DUMMY P4DUMMY P5DUMMY P6DUMMY P8DUMMY P9DUMMY P10DUMMY
  P11DUMMY P12DUMMY P13DUMMY P14DUMMY P15DUMMY P16DUMMY P17DUMMY P18DUMMY
  P19DUMMY P20DUMMY P21DUMMY P22DUMMY P23DUMMY P24DUMMY        P25DUMMY P26DUMMY
  P27DUMMY P28DUMMY P29DUMMY P30DUMMY P31DUMMY P32DUMMY P33DUMMY P34DUMMY
  P35DUMMY P36DUMMY P37DUMMY P38DUMMY P39DUMMY;

  ANALYSIS: TYPE IS MEANSTRUCTURE;

  MODEL:
      ic ON leg wich schw
      P2DUMMY P3DUMMY P4DUMMY P5DUMMY P6DUMMY P8DUMMY P9DUMMY P10DUMMY
      P11DUMMY P12DUMMY P13DUMMY P14DUMMY P15DUMMY P16DUMMY P17DUMMY P18DUMMY
      P19DUMMY P20DUMMY P21DUMMY P22DUMMY P23DUMMY P24DUMMY P25DUMMY P26DUMMY
      P27DUMMY P28DUMMY P29DUMMY P30DUMMY P31DUMMY P32DUMMY P33DUMMY P34DUMMY
      P35DUMMY P36DUMMY P37DUMMY P38DUMMY P39DUMMY;
      leg ON wich
      P2DUMMY P3DUMMY P4DUMMY P5DUMMY P6DUMMY P8DUMMY P9DUMMY P10DUMMY
      P11DUMMY P12DUMMY P13DUMMY P14DUMMY P15DUMMY P16DUMMY P17DUMMY P18DUMMY
      P19DUMMY P20DUMMY P21DUMMY P22DUMMY P23DUMMY P24DUMMY P25DUMMY P26DUMMY
      P27DUMMY P28DUMMY P29DUMMY P30DUMMY P31DUMMY P32DUMMY P33DUMMY P34DUMMY
      P35DUMMY P36DUMMY P37DUMMY P38DUMMY P39DUMMY;
      [ic leg];

  OUTPUT:
```

```
Tech4;
```

```
Mplus VERSION 1.04                                                PAGE    2



INPUT READING TERMINATED NORMALLY



Simultanes Mehrgleichungsmodell fuer die Beziehung
zwischen IC, LEG, WICH und SCHW (mit WICH --> LEG)

Stichprobe: Fragen U + PEIP, disaggregrierte Daten

Mplus VERSION 1.04                                                PAGE    3
Simultanes Mehrgleichungsmodell fuer die Beziehung

SUMMARY OF ANALYSIS

Number of groups                                 1
Number of observations                        1786

Number of y-variables                            2
Number of x-variables                           39
Number of continuous latent variables            0

Observed variables in the analysis
   IC          LEG         WICH        SCHW        P2DUMMY     P3DUMMY
   P4DUMMY     P5DUMMY     P6DUMMY     P8DUMMY     P9DUMMY     P10DUMMY
   P11DUMMY    P12DUMMY    P13DUMMY    P14DUMMY    P15DUMMY    P16DUMMY
   P17DUMMY    P18DUMMY    P19DUMMY    P20DUMMY    P21DUMMY    P22DUMMY
   P23DUMMY    P24DUMMY    P25DUMMY    P26DUMMY    P27DUMMY    P28DUMMY
   P29DUMMY    P30DUMMY    P31DUMMY    P32DUMMY    P33DUMMY    P34DUMMY
   P35DUMMY    P36DUMMY    P37DUMMY    P38DUMMY    P39DUMMY


Estimator                                       ML
Maximum number of iterations                  1000
Convergence criterion                    .500D-04

Input data file(s)
  dummy_pers.dat

Input data format  FREE



THE MODEL ESTIMATION TERMINATED NORMALLY
```

```
TESTS OF MODEL FIT

Chi-Square Test of Model Fit

          Value                     9.735
          Degrees of Freedom            1
          P-Value                   .0018

Loglikelihood

          H0 Value              13874.508
          H1 Value              13879.375

Information Criteria

          Number of Free Parameters             82
          Akaike (AIC)                  -27585.015
          Bayesian (BIC)                -27135.021
          Sample-Size Adjusted BIC      -27395.530
            (n* = (n + 2) / 24)

RMSEA (Root Mean Square Error Of Approximation)
```



```
          Estimate                     .070
          90 Percent C.I.              .035   .113
          Probability RMSEA <= .05     .157



MODEL RESULTS

                   Estimates     S.E.  Est./S.E.

 IC       ON
    LEG               -.457     .027    -16.740
    WICH              -.055     .029     -1.915
    SCHW               .159     .020      7.771
    P2DUMMY            .227     .425       .534
    P3DUMMY           4.017     .431      9.329
    P4DUMMY           2.510     .438      5.732
    P5DUMMY          -4.084     .436     -9.369
    P6DUMMY           1.143     .433      2.640
    P8DUMMY           1.183     .430      2.748
    P9DUMMY            .288     .431       .669
    P10DUMMY          -.838     .428     -1.958
    P11DUMMY          -.924     .444     -2.080
```

P12DUMMY	2.123	.435	4.878
P13DUMMY	2.980	.426	6.988
P14DUMMY	-1.800	.422	-4.262
P15DUMMY	-2.024	.423	-4.785
P16DUMMY	-1.369	.428	-3.196
P17DUMMY	2.383	.435	5.480
P18DUMMY	-3.933	.429	-9.160
P19DUMMY	-3.760	.431	-8.725
P20DUMMY	2.033	.430	4.723
P21DUMMY	.132	.429	.308
P22DUMMY	2.578	.435	5.920
P23DUMMY	-.725	.437	-1.657
P24DUMMY	.862	.425	2.030
P25DUMMY	2.059	.428	4.815
P26DUMMY	-2.206	.431	-5.122
P27DUMMY	2.925	.424	6.897
P28DUMMY	.173	.426	.407
P29DUMMY	2.928	.434	6.750
P30DUMMY	-5.087	.431	-11.801
P31DUMMY	-.143	.438	-.327
P32DUMMY	-.659	.424	-1.555
P33DUMMY	-.027	.436	-.061
P34DUMMY	-1.218	.423	-2.878
P35DUMMY	.166	.428	.389
P36DUMMY	2.028	.435	4.659
P37DUMMY	2.833	.439	6.457
P38DUMMY	3.094	.431	7.173
P39DUMMY	1.460	.425	3.435
LEG ON			
WICH	.839	.015	56.354
P2DUMMY	-.157	.367	-.428
P3DUMMY	-.973	.372	-2.616
P4DUMMY	.142	.378	.375
P5DUMMY	.959	.377	2.546
P6DUMMY	3.470	.366	9.474
P8DUMMY	.237	.371	.639
P9DUMMY	-.739	.369	-2.002
P10DUMMY	.841	.370	2.275
P11DUMMY	4.806	.368	13.051
P12DUMMY	1.429	.375	3.808
P13DUMMY	-1.544	.368	-4.200
P14DUMMY	.498	.366	1.360
P15DUMMY	.244	.367	.666
P16DUMMY	1.705	.369	4.618
P17DUMMY	-.247	.374	-.659
P18DUMMY	-.025	.371	-.067
P19DUMMY	.245	.372	.661
P20DUMMY	-.700	.373	-1.878
P21DUMMY	-.683	.372	-1.837
P22DUMMY	-.252	.378	-.668
P23DUMMY	1.574	.375	4.195

P24DUMMY	1.069	.367	2.911
P25DUMMY	.860	.370	2.322
P26DUMMY	.305	.373	.817
P27DUMMY	-1.146	.367	-3.124
P28DUMMY	-.985	.368	-2.675
P29DUMMY	.217	.376	.578
P30DUMMY	.599	.373	1.606
P31DUMMY	.714	.374	1.909
P32DUMMY	.187	.367	.508
P33DUMMY	.197	.375	.527
P34DUMMY	-.106	.367	-.288
P35DUMMY	-.089	.369	-.242
P36DUMMY	.516	.377	1.370
P37DUMMY	-.608	.377	-1.616
P38DUMMY	.096	.374	.258
P39DUMMY	.356	.369	.966
Residual Variances			
IC	4.150	.139	29.883
LEG	3.122	.104	29.883
Intercepts			
IC	5.974	.328	18.185
LEG	.373	.280	1.330

TECHNICAL 4 OUTPUT

ESTIMATES DERIVED FROM THE MODEL

ESTIMATED COVARIANCE MATRIX FOR THE LATENT VARIABLES

	IC	LEG	WICH	SCHW	P2DUMMY
IC	13.528				
LEG	-7.066	11.795			
WICH	-5.069	8.635	10.179		
SCHW	2.027	-.633	-.487	7.972	
P2DUMMY	-.018	.016	.035	-.046	.026
P3DUMMY	.114	-.047	-.015	-.037	-.001
P4DUMMY	.077	-.055	-.059	-.060	-.001
P5DUMMY	-.107	-.026	-.050	-.039	-.001
P6DUMMY	-.043	.127	.054	-.026	-.001
P8DUMMY	.035	-.007	-.005	.054	-.001
P9DUMMY	.017	-.015	.016	.075	-.001
P10DUMMY	-.034	.019	.007	.030	-.001
P11DUMMY	-.096	.139	.025	.008	-.001
P12DUMMY	.046	-.005	-.040	-.040	-.001
P13DUMMY	.072	-.021	.034	-.037	-.001
P14DUMMY	-.087	.053	.058	-.026	-.001
P15DUMMY	-.086	.038	.048	-.028	-.001
P16DUMMY	-.065	.046	.012	.002	-.001

P17DUMMY	.086	-.042	-.032	.066	-.001
P18DUMMY	-.112	-.015	-.006	-.051	-.001
P19DUMMY	-.111	-.011	-.011	-.065	-.001
P20DUMMY	.070	-.043	-.019	.019	-.001
P21DUMMY	.015	-.038	-.013	.007	-.001
P22DUMMY	.092	-.063	-.057	.002	-.001
P23DUMMY	-.035	-.001	-.040	-.066	-.001
P24DUMMY	-.009	.053	.040	.014	-.001
P25DUMMY	.040	.016	.003	.006	-.001
P26DUMMY	-.057	-.022	-.025	-.016	-.001
P27DUMMY	.068	.000	.047	.009	-.001
P28DUMMY	.004	-.014	.025	.014	-.001
P29DUMMY	.090	-.042	-.046	-.008	-.001
P30DUMMY	-.131	-.012	-.022	.026	-.001
P31DUMMY	.012	-.016	-.031	.090	-.001
P32DUMMY	-.040	.026	.035	-.005	-.001
P33DUMMY	.020	-.034	-.036	.072	-.001
P34DUMMY	-.052	.024	.043	.009	-.001
P35DUMMY	.003	.001	.015	.048	-.001
P36DUMMY	.062	-.040	-.053	-.028	-.001
P37DUMMY	.112	-.066	-.049	.075	-.001
P38DUMMY	.084	-.030	-.028	-.033	-.001
P39DUMMY	.021	.018	.021	-.002	-.001

ESTIMATED COVARIANCE MATRIX FOR THE LATENT VARIABLES

	P3DUMMY	P4DUMMY	P5DUMMY	P6DUMMY	P8DUMMY
P3DUMMY	.026				
P4DUMMY	-.001	.026			
P5DUMMY	-.001	-.001	.026		
P6DUMMY	-.001	-.001	-.001	.026	
P8DUMMY	-.001	-.001	-.001	-.001	.026
P9DUMMY	-.001	-.001	-.001	-.001	-.001
P10DUMMY	-.001	-.001	-.001	-.001	-.001
P11DUMMY	-.001	-.001	-.001	-.001	-.001
P12DUMMY	-.001	-.001	-.001	-.001	-.001
P13DUMMY	-.001	-.001	-.001	-.001	-.001
P14DUMMY	-.001	-.001	-.001	-.001	-.001
P15DUMMY	-.001	-.001	-.001	-.001	-.001
P16DUMMY	-.001	-.001	-.001	-.001	-.001
P17DUMMY	-.001	-.001	-.001	-.001	-.001
P18DUMMY	-.001	-.001	-.001	-.001	-.001
P19DUMMY	-.001	-.001	-.001	-.001	-.001
P20DUMMY	-.001	-.001	-.001	-.001	-.001
P21DUMMY	-.001	-.001	-.001	-.001	-.001
P22DUMMY	-.001	-.001	-.001	-.001	-.001
P23DUMMY	-.001	-.001	-.001	-.001	-.001
P24DUMMY	-.001	-.001	-.001	-.001	-.001
P25DUMMY	-.001	-.001	-.001	-.001	-.001
P26DUMMY	-.001	-.001	-.001	-.001	-.001

P27DUMMY	-.001	-.001	-.001	-.001	-.001
P28DUMMY	-.001	-.001	-.001	-.001	-.001
P29DUMMY	-.001	-.001	-.001	-.001	-.001
P30DUMMY	-.001	-.001	-.001	-.001	-.001
P31DUMMY	-.001	-.001	-.001	-.001	-.001
P32DUMMY	-.001	-.001	-.001	-.001	-.001
P33DUMMY	-.001	-.001	-.001	-.001	-.001
P34DUMMY	-.001	-.001	-.001	-.001	-.001
P35DUMMY	-.001	-.001	-.001	-.001	-.001
P36DUMMY	-.001	-.001	-.001	-.001	-.001
P37DUMMY	-.001	-.001	-.001	-.001	-.001
P38DUMMY	-.001	-.001	-.001	-.001	-.001
P39DUMMY	-.001	-.001	-.001	-.001	-.001

ESTIMATED COVARIANCE MATRIX FOR THE LATENT VARIABLES

	P9DUMMY	P10DUMMY	P11DUMMY	P12DUMMY	P13DUMMY
P9DUMMY	.026				
P10DUMMY	-.001	.026			
P11DUMMY	-.001	-.001	.026		
P12DUMMY	-.001	-.001	-.001	.026	
P13DUMMY	-.001	-.001	-.001	-.001	.026
P14DUMMY	-.001	-.001	-.001	-.001	-.001
P15DUMMY	-.001	-.001	-.001	-.001	-.001
P16DUMMY	-.001	-.001	-.001	-.001	-.001
P17DUMMY	-.001	-.001	-.001	-.001	-.001
P18DUMMY	-.001	-.001	-.001	-.001	-.001
P19DUMMY	-.001	-.001	-.001	-.001	-.001
P20DUMMY	-.001	-.001	-.001	-.001	-.001
P21DUMMY	-.001	-.001	-.001	-.001	-.001
P22DUMMY	-.001	-.001	-.001	-.001	-.001
P23DUMMY	-.001	-.001	-.001	-.001	-.001
P24DUMMY	-.001	-.001	-.001	-.001	-.001
P25DUMMY	-.001	-.001	-.001	-.001	-.001
P26DUMMY	-.001	-.001	-.001	-.001	-.001
P27DUMMY	-.001	-.001	-.001	-.001	-.001
P28DUMMY	-.001	-.001	-.001	-.001	-.001
P29DUMMY	-.001	-.001	-.001	-.001	-.001
P30DUMMY	-.001	-.001	-.001	-.001	-.001
P31DUMMY	-.001	-.001	-.001	-.001	-.001
P32DUMMY	-.001	-.001	-.001	-.001	-.001
P33DUMMY	-.001	-.001	-.001	-.001	-.001
P34DUMMY	-.001	-.001	-.001	-.001	-.001
P35DUMMY	-.001	-.001	-.001	-.001	-.001
P36DUMMY	-.001	-.001	-.001	-.001	-.001
P37DUMMY	-.001	-.001	-.001	-.001	-.001
P38DUMMY	-.001	-.001	-.001	-.001	-.001
P39DUMMY	-.001	-.001	-.001	-.001	-.001

ESTIMATED COVARIANCE MATRIX FOR THE LATENT VARIABLES

	P14DUMMY	P15DUMMY	P16DUMMY	P17DUMMY	P18DUMMY
P14DUMMY	.026				
P15DUMMY	-.001	.026			
P16DUMMY	-.001	-.001	.026		
P17DUMMY	-.001	-.001	-.001	.026	
P18DUMMY	-.001	-.001	-.001	-.001	.026
P19DUMMY	-.001	-.001	-.001	-.001	-.001
P20DUMMY	-.001	-.001	-.001	-.001	-.001
P21DUMMY	-.001	-.001	-.001	-.001	-.001
P22DUMMY	-.001	-.001	-.001	-.001	-.001
P23DUMMY	-.001	-.001	-.001	-.001	-.001
P24DUMMY	-.001	-.001	-.001	-.001	-.001
P25DUMMY	-.001	-.001	-.001	-.001	-.001
P26DUMMY	-.001	-.001	-.001	-.001	-.001
P27DUMMY	-.001	-.001	-.001	-.001	-.001
P28DUMMY	-.001	-.001	-.001	-.001	-.001
P29DUMMY	-.001	-.001	-.001	-.001	-.001
P30DUMMY	-.001	-.001	-.001	-.001	-.001
P31DUMMY	-.001	-.001	-.001	-.001	-.001
P32DUMMY	-.001	-.001	-.001	-.001	-.001
P33DUMMY	-.001	-.001	-.001	-.001	-.001
P34DUMMY	-.001	-.001	-.001	-.001	-.001
P35DUMMY	-.001	-.001	-.001	-.001	-.001
P36DUMMY	-.001	-.001	-.001	-.001	-.001
P37DUMMY	-.001	-.001	-.001	-.001	-.001
P38DUMMY	-.001	-.001	-.001	-.001	-.001
P39DUMMY	-.001	-.001	-.001	-.001	-.001

ESTIMATED COVARIANCE MATRIX FOR THE LATENT VARIABLES

	P19DUMMY	P20DUMMY	P21DUMMY	P22DUMMY	P23DUMMY
P19DUMMY	.026				
P20DUMMY	-.001	.026			
P21DUMMY	-.001	-.001	.026		
P22DUMMY	-.001	-.001	-.001	.026	
P23DUMMY	-.001	-.001	-.001	-.001	.026
P24DUMMY	-.001	-.001	-.001	-.001	-.001
P25DUMMY	-.001	-.001	-.001	-.001	-.001
P26DUMMY	-.001	-.001	-.001	-.001	-.001
P27DUMMY	-.001	-.001	-.001	-.001	-.001
P28DUMMY	-.001	-.001	-.001	-.001	-.001
P29DUMMY	-.001	-.001	-.001	-.001	-.001
P30DUMMY	-.001	-.001	-.001	-.001	-.001
P31DUMMY	-.001	-.001	-.001	-.001	-.001
P32DUMMY	-.001	-.001	-.001	-.001	-.001
P33DUMMY	-.001	-.001	-.001	-.001	-.001
P34DUMMY	-.001	-.001	-.001	-.001	-.001
P35DUMMY	-.001	-.001	-.001	-.001	-.001
P36DUMMY	-.001	-.001	-.001	-.001	-.001

P37DUMMY	-.001	-.001	-.001	-.001	-.001
P38DUMMY	-.001	-.001	-.001	-.001	-.001
P39DUMMY	-.001	-.001	-.001	-.001	-.001

ESTIMATED COVARIANCE MATRIX FOR THE LATENT VARIABLES

	P24DUMMY	P25DUMMY	P26DUMMY	P27DUMMY	P28DUMMY
P24DUMMY	.026				
P25DUMMY	-.001	.026			
P26DUMMY	-.001	-.001	.026		
P27DUMMY	-.001	-.001	-.001	.026	
P28DUMMY	-.001	-.001	-.001	-.001	.026
P29DUMMY	-.001	-.001	-.001	-.001	-.001
P30DUMMY	-.001	-.001	-.001	-.001	-.001
P31DUMMY	-.001	-.001	-.001	-.001	-.001
P32DUMMY	-.001	-.001	-.001	-.001	-.001
P33DUMMY	-.001	-.001	-.001	-.001	-.001
P34DUMMY	-.001	-.001	-.001	-.001	-.001
P35DUMMY	-.001	-.001	-.001	-.001	-.001
P36DUMMY	-.001	-.001	-.001	-.001	-.001
P37DUMMY	-.001	-.001	-.001	-.001	-.001
P38DUMMY	-.001	-.001	-.001	-.001	-.001
P39DUMMY	-.001	-.001	-.001	-.001	-.001

ESTIMATED COVARIANCE MATRIX FOR THE LATENT VARIABLES

	P29DUMMY	P30DUMMY	P31DUMMY	P32DUMMY	P33DUMMY
P29DUMMY	.026				
P30DUMMY	-.001	.026			
P31DUMMY	-.001	-.001	.026		
P32DUMMY	-.001	-.001	-.001	.026	
P33DUMMY	-.001	-.001	-.001	-.001	.026
P34DUMMY	-.001	-.001	-.001	-.001	-.001
P35DUMMY	-.001	-.001	-.001	-.001	-.001
P36DUMMY	-.001	-.001	-.001	-.001	-.001
P37DUMMY	-.001	-.001	-.001	-.001	-.001
P38DUMMY	-.001	-.001	-.001	-.001	-.001
P39DUMMY	-.001	-.001	-.001	-.001	-.001

ESTIMATED COVARIANCE MATRIX FOR THE LATENT VARIABLES

	P34DUMMY	P35DUMMY	P36DUMMY	P37DUMMY	P38DUMMY
P34DUMMY	.026				
P35DUMMY	-.001	.026			
P36DUMMY	-.001	-.001	.026		
P37DUMMY	-.001	-.001	-.001	.026	

```
 P38DUMMY       -.001         -.001         -.001         -.001           .026
 P39DUMMY       -.001         -.001         -.001         -.001          -.001


           ESTIMATED COVARIANCE MATRIX FOR THE LATENT VARIABLES
              P39DUMMY
              ________
 P39DUMMY        .026



     Beginning Time:  15:45:47
        Ending Time:  15:45:53
Mplus VERSION 1.04                                                   PAGE   10
Simultanes Mehrgleichungsmodell fuer die Beziehung

       Elapsed Time:  00:00:06
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C3c: Group B (pepr & pd questions)

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Mplus VERSION 1.04
MUTHEN & MUTHEN
02/02/2001   3:51 PM

INPUT INSTRUCTIONS

  TITLE: Simultanes Mehrgleichungsmodell fuer die Beziehung
  zwischen IC, LEG, WICH und SCHW (mit WICH --> LEG)

  Stichprobe: Fragen PDD, PDI + PEPR, disaggregrierte Daten

  DATA: FILE IS dummy_prod.dat;

  VARIABLE: NAMES ARE

  LEG SCHW WICH IC
  P1DUMMY P2DUMMY P3DUMMY P4DUMMY P5DUMMY P6DUMMY P8DUMMY P9DUMMY P10DUMMY
  P11DUMMY P12DUMMY P13DUMMY P14DUMMY P15DUMMY P16DUMMY P17DUMMY P18DUMMY
  P19DUMMY P20DUMMY P21DUMMY P22DUMMY P23DUMMY P24DUMMY        P25DUMMY P26DUMMY
  P27DUMMY P28DUMMY P29DUMMY P30DUMMY P31DUMMY P32DUMMY P33DUMMY P34DUMMY
  P35DUMMY P36DUMMY P37DUMMY P38DUMMY P39DUMMY;

  USEVARIABLES IC LEG WICH SCHW
  P2DUMMY P3DUMMY P4DUMMY P5DUMMY P6DUMMY P8DUMMY P9DUMMY P10DUMMY
  P11DUMMY P12DUMMY P13DUMMY P14DUMMY P15DUMMY P16DUMMY P17DUMMY P18DUMMY
  P19DUMMY P20DUMMY P21DUMMY P22DUMMY P23DUMMY P24DUMMY        P25DUMMY P26DUMMY
  P27DUMMY P28DUMMY P29DUMMY P30DUMMY P31DUMMY P32DUMMY P33DUMMY P34DUMMY
  P35DUMMY P36DUMMY P37DUMMY P38DUMMY P39DUMMY;

  ANALYSIS: TYPE IS MEANSTRUCTURE;

  MODEL:
      ic ON leg wich schw
      P2DUMMY P3DUMMY P4DUMMY P5DUMMY P6DUMMY P8DUMMY P9DUMMY P10DUMMY
      P11DUMMY P12DUMMY P13DUMMY P14DUMMY P15DUMMY P16DUMMY P17DUMMY P18DUMMY
      P19DUMMY P20DUMMY P21DUMMY P22DUMMY P23DUMMY P24DUMMY P25DUMMY P26DUMMY
      P27DUMMY P28DUMMY P29DUMMY P30DUMMY P31DUMMY P32DUMMY P33DUMMY P34DUMMY
      P35DUMMY P36DUMMY P37DUMMY P38DUMMY P39DUMMY;
      leg ON wich
      P2DUMMY P3DUMMY P4DUMMY P5DUMMY P6DUMMY P8DUMMY P9DUMMY P10DUMMY
      P11DUMMY P12DUMMY P13DUMMY P14DUMMY P15DUMMY P16DUMMY P17DUMMY P18DUMMY
      P19DUMMY P20DUMMY P21DUMMY P22DUMMY P23DUMMY P24DUMMY P25DUMMY P26DUMMY
      P27DUMMY P28DUMMY P29DUMMY P30DUMMY P31DUMMY P32DUMMY P33DUMMY P34DUMMY
      P35DUMMY P36DUMMY P37DUMMY P38DUMMY P39DUMMY;
      [ic leg];

  OUTPUT:
```

```
Tech4;
```

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Mplus VERSION 1.04                                            PAGE    2


INPUT READING TERMINATED NORMALLY



Simultanes Mehrgleichungsmodell fuer die Beziehung
zwischen IC, LEG, WICH und SCHW (mit WICH --> LEG)

Stichprobe: Fragen PDD, PDI + PEPR, disaggregrierte Daten

SUMMARY OF ANALYSIS

Mplus VERSION 1.04                                            PAGE    3
Simultanes Mehrgleichungsmodell fuer die Beziehung

Number of groups                                   1
Number of observations                          2470

Number of y-variables                              2
Number of x-variables                             39
Number of continuous latent variables              0

Observed variables in the analysis
   IC          LEG         WICH        SCHW        P2DUMMY     P3DUMMY
   P4DUMMY     P5DUMMY     P6DUMMY     P8DUMMY     P9DUMMY     P10DUMMY
   P11DUMMY    P12DUMMY    P13DUMMY    P14DUMMY    P15DUMMY    P16DUMMY
   P17DUMMY    P18DUMMY    P19DUMMY    P20DUMMY    P21DUMMY    P22DUMMY
   P23DUMMY    P24DUMMY    P25DUMMY    P26DUMMY    P27DUMMY    P28DUMMY
   P29DUMMY    P30DUMMY    P31DUMMY    P32DUMMY    P33DUMMY    P34DUMMY
   P35DUMMY    P36DUMMY    P37DUMMY    P38DUMMY    P39DUMMY


Estimator                                         ML
Maximum number of iterations                    1000
Convergence criterion                        .500D-04

Input data file(s)
  dummy_prod.dat

Input data format  FREE



THE MODEL ESTIMATION TERMINATED NORMALLY
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TESTS OF MODEL FIT

Chi-Square Test of Model Fit

          Value                     4.340
          Degrees of Freedom            1
          P-Value                   .0372

Loglikelihood

          H0 Value              20369.999
          H1 Value              20372.169

Information Criteria

          Number of Free Parameters             82
          Akaike (AIC)                  -40575.998
          Bayesian (BIC)                -40099.416
          Sample-Size Adjusted BIC      -40359.950
            (n* = (n + 2) / 24)

RMSEA (Root Mean Square Error Of Approximation)

          Estimate                        .037
          90 Percent C.I.                 .007   .075
Mplus VERSION 1.04                                                  PAGE    4
Simultanes Mehrgleichungsmodell fuer die Beziehung

          Probability RMSEA <= .05        .656



MODEL RESULTS

                   Estimates     S.E.  Est./S.E.

 IC       ON
    LEG               -.397      .022    -18.224
    WICH               .003      .019       .142
    SCHW               .182      .016     11.248
    P2DUMMY          -1.986      .303     -6.560
    P3DUMMY            .859      .305      2.820
    P4DUMMY           -.082      .309      -.265
    P5DUMMY          -2.250      .304     -7.393
    P6DUMMY           -.300      .303      -.988
    P8DUMMY           -.737      .301     -2.444
    P9DUMMY           1.973      .303      6.512
    P10DUMMY         -1.239      .303     -4.095
    P11DUMMY         -1.008      .307     -3.283
    P12DUMMY          -.452      .302     -1.497
    P13DUMMY           .758      .302      2.509
    P14DUMMY           .061      .301       .203
```

P15DUMMY	-1.188	.304	-3.907
P16DUMMY	-1.523	.302	-5.036
P17DUMMY	-.119	.310	-.385
P18DUMMY	-1.944	.302	-6.429
P19DUMMY	-3.172	.308	-10.285
P20DUMMY	-.243	.305	-.797
P21DUMMY	.201	.303	.663
P22DUMMY	-1.483	.303	-4.895
P23DUMMY	-1.638	.304	-5.380
P24DUMMY	-.853	.302	-2.827
P25DUMMY	.984	.302	3.265
P26DUMMY	-.252	.302	-.834
P27DUMMY	-.774	.303	-2.558
P28DUMMY	-1.178	.303	-3.894
P29DUMMY	-1.272	.305	-4.165
P30DUMMY	-3.355	.308	-10.899
P31DUMMY	.935	.306	3.056
P32DUMMY	-1.732	.305	-5.669
P33DUMMY	-1.406	.302	-4.664
P34DUMMY	-1.457	.302	-4.820
P35DUMMY	-1.105	.303	-3.647
P36DUMMY	-.255	.306	-.833
P37DUMMY	1.289	.307	4.196
P38DUMMY	.264	.302	.876
P39DUMMY	.512	.302	1.692
LEG ON			
WICH	.591	.013	46.850
P2DUMMY	-.592	.279	-2.124
P3DUMMY	-.201	.281	-.717
P4DUMMY	-1.420	.284	-5.005
P5DUMMY	.521	.280	1.861
P6DUMMY	1.053	.279	3.770
P8DUMMY	.110	.278	.394
P9DUMMY	-.721	.278	-2.590
P10DUMMY	.161	.279	.578
P11DUMMY	2.056	.280	7.340
P12DUMMY	.646	.279	2.318
P13DUMMY	-.590	.278	-2.122
P14DUMMY	-.033	.278	-.118
P15DUMMY	-1.454	.279	-5.212
P16DUMMY	-.259	.279	-.930
P17DUMMY	-1.947	.283	-6.892
P18DUMMY	.179	.279	.644
P19DUMMY	-1.278	.282	-4.529
P20DUMMY	-.592	.279	-2.119
P21DUMMY	-.990	.279	-3.545
P22DUMMY	-.618	.279	-2.211
P23DUMMY	.505	.279	1.810
P24DUMMY	.077	.279	.278
P25DUMMY	-.190	.278	-.681
P26DUMMY	-.510	.278	-1.831

P27DUMMY	.519	.279	1.858
P28DUMMY	-1.157	.278	-4.155
P29DUMMY	1.678	.280	6.000
P30DUMMY	.158	.284	.556
P31DUMMY	-1.004	.281	-3.574
P32DUMMY	-1.368	.281	-4.876
P33DUMMY	.072	.278	.259
P34DUMMY	.215	.278	.773
P35DUMMY	-.204	.280	-.731
P36DUMMY	.083	.283	.295
P37DUMMY	-1.496	.279	-5.369
P38DUMMY	.196	.278	.702
P39DUMMY	-.398	.279	-1.429
Residual Variances			
IC	2.951	.084	35.143
LEG	2.517	.072	35.143
Intercepts			
IC	5.235	.265	19.754
LEG	3.970	.225	17.671

TECHNICAL 4 OUTPUT

ESTIMATES DERIVED FROM THE MODEL

ESTIMATED COVARIANCE MATRIX FOR THE LATENT VARIABLES

	IC	LEG	WICH	SCHW	P2DUMMY
IC	5.681				
LEG	-2.555	6.198			
WICH	-1.736	4.869	7.977		
SCHW	1.771	-.862	-1.286	5.938	
P2DUMMY	-.042	-.001	.014	-.040	.026
P3DUMMY	.045	-.021	-.037	-.019	-.001
P4DUMMY	.042	-.072	-.069	-.012	-.001
P5DUMMY	-.052	.007	-.021	-.037	-.001
P6DUMMY	-.004	.031	-.005	-.009	-.001
P8DUMMY	-.014	.028	.032	-.005	-.001
P9DUMMY	.073	.006	.032	.031	-.001
P10DUMMY	-.017	.008	-.003	.010	-.001
P11DUMMY	-.023	.047	-.022	.028	-.001
P12DUMMY	-.009	.033	.017	-.008	-.001
P13DUMMY	.022	.021	.052	-.038	-.001
P14DUMMY	.004	.027	.037	-.021	-.001
P15DUMMY	-.007	-.029	.005	-.026	-.001
P16DUMMY	-.021	.003	.007	.018	-.001
P17DUMMY	.053	-.079	-.057	.043	-.001
P18DUMMY	-.050	.023	.020	-.041	-.001
P19DUMMY	-.051	-.059	-.052	-.047	-.001

P20DUMMY	.025	-.010	-.001	.056	-.001
P21DUMMY	.029	-.024	-.006	-.015	-.001
P22DUMMY	-.015	-.013	-.005	.009	-.001
P23DUMMY	-.043	.016	-.005	-.057	-.001
P24DUMMY	-.011	.019	.019	.011	-.001
P25DUMMY	.034	.018	.029	-.014	-.001
P26DUMMY	.004	.010	.029	-.015	-.001
P27DUMMY	-.008	.018	-.002	.011	-.001
P28DUMMY	-.009	-.009	.027	.004	-.001
P29DUMMY	-.029	.043	-.013	.021	-.001
P30DUMMY	-.052	-.032	-.072	.032	-.001
P31DUMMY	.065	-.042	-.036	.036	-.001
P32DUMMY	-.007	-.048	-.031	.014	-.001
P33DUMMY	-.033	.025	.029	-.018	-.001
P34DUMMY	-.036	.047	.059	.020	-.001
P35DUMMY	-.006	-.006	-.011	.017	-.001
P36DUMMY	.022	-.025	-.057	.006	-.001
P37DUMMY	.074	-.024	.016	.069	-.001
P38DUMMY	.010	.025	.022	-.023	-.001
P39DUMMY	.033	.004	.014	.020	-.001

ESTIMATED COVARIANCE MATRIX FOR THE LATENT VARIABLES

	P3DUMMY	P4DUMMY	P5DUMMY	P6DUMMY	P8DUMMY
P3DUMMY	.026				
P4DUMMY	-.001	.026			
P5DUMMY	-.001	-.001	.026		
P6DUMMY	-.001	-.001	-.001	.026	
P8DUMMY	-.001	-.001	-.001	-.001	.026
P9DUMMY	-.001	-.001	-.001	-.001	-.001
P10DUMMY	-.001	-.001	-.001	-.001	-.001
P11DUMMY	-.001	-.001	-.001	-.001	-.001
P12DUMMY	-.001	-.001	-.001	-.001	-.001
P13DUMMY	-.001	-.001	-.001	-.001	-.001
P14DUMMY	-.001	-.001	-.001	-.001	-.001
P15DUMMY	-.001	-.001	-.001	-.001	-.001
P16DUMMY	-.001	-.001	-.001	-.001	-.001
P17DUMMY	-.001	-.001	-.001	-.001	-.001
P18DUMMY	-.001	-.001	-.001	-.001	-.001
P19DUMMY	-.001	-.001	-.001	-.001	-.001
P20DUMMY	-.001	-.001	-.001	-.001	-.001
P21DUMMY	-.001	-.001	-.001	-.001	-.001
P22DUMMY	-.001	-.001	-.001	-.001	-.001
P23DUMMY	-.001	-.001	-.001	-.001	-.001
P24DUMMY	-.001	-.001	-.001	-.001	-.001
P25DUMMY	-.001	-.001	-.001	-.001	-.001
P26DUMMY	-.001	-.001	-.001	-.001	-.001

P27DUMMY	-.001	-.001	-.001	-.001	-.001
P28DUMMY	-.001	-.001	-.001	-.001	-.001
P29DUMMY	-.001	-.001	-.001	-.001	-.001
P30DUMMY	-.001	-.001	-.001	-.001	-.001
P31DUMMY	-.001	-.001	-.001	-.001	-.001
P32DUMMY	-.001	-.001	-.001	-.001	-.001
P33DUMMY	-.001	-.001	-.001	-.001	-.001
P34DUMMY	-.001	-.001	-.001	-.001	-.001
P35DUMMY	-.001	-.001	-.001	-.001	-.001
P36DUMMY	-.001	-.001	-.001	-.001	-.001
P37DUMMY	-.001	-.001	-.001	-.001	-.001
P38DUMMY	-.001	-.001	-.001	-.001	-.001
P39DUMMY	-.001	-.001	-.001	-.001	-.001

ESTIMATED COVARIANCE MATRIX FOR THE LATENT VARIABLES

	P9DUMMY	P10DUMMY	P11DUMMY	P12DUMMY	P13DUMMY
P9DUMMY	.026				
P10DUMMY	-.001	.026			
P11DUMMY	-.001	-.001	.026		
P12DUMMY	-.001	-.001	-.001	.026	
P13DUMMY	-.001	-.001	-.001	-.001	.026
P14DUMMY	-.001	-.001	-.001	-.001	-.001
P15DUMMY	-.001	-.001	-.001	-.001	-.001
P16DUMMY	-.001	-.001	-.001	-.001	-.001
P17DUMMY	-.001	-.001	-.001	-.001	-.001
P18DUMMY	-.001	-.001	-.001	-.001	-.001
P19DUMMY	-.001	-.001	-.001	-.001	-.001
P20DUMMY	-.001	-.001	-.001	-.001	-.001
P21DUMMY	-.001	-.001	-.001	-.001	-.001
P22DUMMY	-.001	-.001	-.001	-.001	-.001
P23DUMMY	-.001	-.001	-.001	-.001	-.001
P24DUMMY	-.001	-.001	-.001	-.001	-.001
P25DUMMY	-.001	-.001	-.001	-.001	-.001
P26DUMMY	-.001	-.001	-.001	-.001	-.001
P27DUMMY	-.001	-.001	-.001	-.001	-.001
P28DUMMY	-.001	-.001	-.001	-.001	-.001
P29DUMMY	-.001	-.001	-.001	-.001	-.001
P30DUMMY	-.001	-.001	-.001	-.001	-.001
P31DUMMY	-.001	-.001	-.001	-.001	-.001
P32DUMMY	-.001	-.001	-.001	-.001	-.001
P33DUMMY	-.001	-.001	-.001	-.001	-.001
P34DUMMY	-.001	-.001	-.001	-.001	-.001
P35DUMMY	-.001	-.001	-.001	-.001	-.001
P36DUMMY	-.001	-.001	-.001	-.001	-.001
P37DUMMY	-.001	-.001	-.001	-.001	-.001
P38DUMMY	-.001	-.001	-.001	-.001	-.001
P39DUMMY	-.001	-.001	-.001	-.001	-.001

ESTIMATED COVARIANCE MATRIX FOR THE LATENT VARIABLES

	P14DUMMY	P15DUMMY	P16DUMMY	P17DUMMY	P18DUMMY
P14DUMMY	.026				
P15DUMMY	-.001	.026			
P16DUMMY	-.001	-.001	.026		
P17DUMMY	-.001	-.001	-.001	.026	
P18DUMMY	-.001	-.001	-.001	-.001	.026
P19DUMMY	-.001	-.001	-.001	-.001	-.001
P20DUMMY	-.001	-.001	-.001	-.001	-.001
P21DUMMY	-.001	-.001	-.001	-.001	-.001
P22DUMMY	-.001	-.001	-.001	-.001	-.001
P23DUMMY	-.001	-.001	-.001	-.001	-.001
P24DUMMY	-.001	-.001	-.001	-.001	-.001
P25DUMMY	-.001	-.001	-.001	-.001	-.001
P26DUMMY	-.001	-.001	-.001	-.001	-.001
P27DUMMY	-.001	-.001	-.001	-.001	-.001
P28DUMMY	-.001	-.001	-.001	-.001	-.001
P29DUMMY	-.001	-.001	-.001	-.001	-.001
P30DUMMY	-.001	-.001	-.001	-.001	-.001
P31DUMMY	-.001	-.001	-.001	-.001	-.001
P32DUMMY	-.001	-.001	-.001	-.001	-.001
P33DUMMY	-.001	-.001	-.001	-.001	-.001
P34DUMMY	-.001	-.001	-.001	-.001	-.001
P35DUMMY	-.001	-.001	-.001	-.001	-.001
P36DUMMY	-.001	-.001	-.001	-.001	-.001
P37DUMMY	-.001	-.001	-.001	-.001	-.001
P38DUMMY	-.001	-.001	-.001	-.001	-.001
P39DUMMY	-.001	-.001	-.001	-.001	-.001

ESTIMATED COVARIANCE MATRIX FOR THE LATENT VARIABLES

	P19DUMMY	P20DUMMY	P21DUMMY	P22DUMMY	P23DUMMY
P19DUMMY	.026				
P20DUMMY	-.001	.026			
P21DUMMY	-.001	-.001	.026		
P22DUMMY	-.001	-.001	-.001	.026	
P23DUMMY	-.001	-.001	-.001	-.001	.026
P24DUMMY	-.001	-.001	-.001	-.001	-.001
P25DUMMY	-.001	-.001	-.001	-.001	-.001
P26DUMMY	-.001	-.001	-.001	-.001	-.001
P27DUMMY	-.001	-.001	-.001	-.001	-.001
P28DUMMY	-.001	-.001	-.001	-.001	-.001
P29DUMMY	-.001	-.001	-.001	-.001	-.001
P30DUMMY	-.001	-.001	-.001	-.001	-.001
P31DUMMY	-.001	-.001	-.001	-.001	-.001
P32DUMMY	-.001	-.001	-.001	-.001	-.001
P33DUMMY	-.001	-.001	-.001	-.001	-.001
P34DUMMY	-.001	-.001	-.001	-.001	-.001

P35DUMMY	-.001	-.001	-.001	-.001	-.001
P36DUMMY	-.001	-.001	-.001	-.001	-.001
P37DUMMY	-.001	-.001	-.001	-.001	-.001
P38DUMMY	-.001	-.001	-.001	-.001	-.001
P39DUMMY	-.001	-.001	-.001	-.001	-.001

ESTIMATED COVARIANCE MATRIX FOR THE LATENT VARIABLES

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Simultanes Mehrgleichungsmodell fuer die Beziehung

	P24DUMMY	P25DUMMY	P26DUMMY	P27DUMMY	P28DUMMY
P24DUMMY	.026				
P25DUMMY	-.001	.026			
P26DUMMY	-.001	-.001	.026		
P27DUMMY	-.001	-.001	-.001	.026	
P28DUMMY	-.001	-.001	-.001	-.001	.026
P29DUMMY	-.001	-.001	-.001	-.001	-.001
P30DUMMY	-.001	-.001	-.001	-.001	-.001
P31DUMMY	-.001	-.001	-.001	-.001	-.001
P32DUMMY	-.001	-.001	-.001	-.001	-.001
P33DUMMY	-.001	-.001	-.001	-.001	-.001
P34DUMMY	-.001	-.001	-.001	-.001	-.001
P35DUMMY	-.001	-.001	-.001	-.001	-.001
P36DUMMY	-.001	-.001	-.001	-.001	-.001
P37DUMMY	-.001	-.001	-.001	-.001	-.001
P38DUMMY	-.001	-.001	-.001	-.001	-.001
P39DUMMY	-.001	-.001	-.001	-.001	-.001

ESTIMATED COVARIANCE MATRIX FOR THE LATENT VARIABLES

	P29DUMMY	P30DUMMY	P31DUMMY	P32DUMMY	P33DUMMY
P29DUMMY	.026				
P30DUMMY	-.001	.026			
P31DUMMY	-.001	-.001	.026		
P32DUMMY	-.001	-.001	-.001	.026	
P33DUMMY	-.001	-.001	-.001	-.001	.026
P34DUMMY	-.001	-.001	-.001	-.001	-.001
P35DUMMY	-.001	-.001	-.001	-.001	-.001
P36DUMMY	-.001	-.001	-.001	-.001	-.001
P37DUMMY	-.001	-.001	-.001	-.001	-.001
P38DUMMY	-.001	-.001	-.001	-.001	-.001
P39DUMMY	-.001	-.001	-.001	-.001	-.001

ESTIMATED COVARIANCE MATRIX FOR THE LATENT VARIABLES

	P34DUMMY	P35DUMMY	P36DUMMY	P37DUMMY	P38DUMMY
P34DUMMY	.026				
P35DUMMY	-.001	.026			

```
 P36DUMMY       -.001         -.001          .026
 P37DUMMY       -.001         -.001         -.001          .026
 P38DUMMY       -.001         -.001         -.001         -.001          .026
 P39DUMMY       -.001         -.001         -.001         -.001         -.001


           ESTIMATED COVARIANCE MATRIX FOR THE LATENT VARIABLES
              P39DUMMY
              ________
 P39DUMMY        .026



     Beginning Time:  15:51:15
        Ending Time:  15:51:21
       Elapsed Time:  00:00:06

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Simultanes Mehrgleichungsmodell fuer die Beziehung



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C4: Questions employed to derive Privacy Attitudes

1. (CONCERN ON PRIVACY)

Wie starke Sorgen machen Sie sich über die Gefahr einer Einbuße Ihrer Privatheit durch die Nutzung des Internets?

❑ sorge mich sehr
❑ sorge mich ein bisschen
❑ sorge mich nicht so sehr
❑ sorge mich gar nicht

2. (INDEX SCENARIO 1)

Szenario 1: Stellen Sie sich vor, Sie gingen auf die WWW-Seite Ihrer Hausbank und entdeckten ein elektronisches Formular, welches Sie ausfüllen können, um daraufhin auf Sie persönlich zugeschnittene Anlageempfehlungen zu bekommen. Auf dem Formular werden Sie gebeten, Angaben zu Ihrem Einkommen, Ihren gegenwärtigen Anlagen und Sparzielen zu machen. Gleichzeitig werden keine Angaben zu Ihrer Person, Ihrem Namen oder andere Informationen abgefragt, von denen auf Ihre Person geschlossen werden könnte. Ausgehend von den Informationen auf der Website sieht es so aus, als könnten Sie durch das Ausfüllen des Formulars nützliche Informationen bekommen.

Würden Sie das Formular ausfüllen?

❑ Auf gar keinen Fall
❑ Wahrscheinlich nicht
❑ Ich bin nicht sicher
❑ Wahrscheinlich schon
❑ Ganz bestimmt

Wie würden Sie sich in ***Szenario 1*** verhalten, angenommen das Formular würde doch nach Ihrem Namen und Ihrer Adresse fragen, so dass Ihnen die Bank einen Anlageführer zuschicken kann? Nehmen Sie an, daß Sie davon ausgehen, dass dieser Anlageführer für Sie nützlich sein könnte.

Würden Sie die Angaben (Namen und Adresse) machen?

❑ Auf gar keinen Fall
❑ Wahrscheinlich nicht
❑ Ich bin nicht sicher
❑ Wahrscheinlich schon
❑ Ganz bestimmt

2. (INDEX SCENARIO 3)

Szenario 3: Während Sie online Informationen zu einem Ihrer Lieblingshobbies suchen, landen Sie auf einer Website, die ein paar wirklich interessante Informationen enthält. Die Site wird gesponsert von einer Firma, deren Name Sie noch nie gehört haben, aber die Leute scheinen sich auszukennen. Sie finden ein Formular auf der Seite, welches Sie ausfüllen können, um eine kostenlose Broschüre und einige Zusatzinformationen zu erhalten sowie Coupons auf einige Produkte der Firma. Das Formular verlangt Ihren Namen und Ihre Postanschrift. Wie würden Sie voraussichtlich reagieren?

❑ Ich würde die verlangte Information eingeben
❑ Ich würde versuchen, die Firma anzurufen, um so die Broschüre und die Coupons zu bekommen
❑ Ich würde wahrscheinlich auf die Möglichkeit verzichten, die Broschüre und die Coupons zu bekommen

Wie würden Sie Ihr Verhalten in ***Szenario 3*** ändern, enthielte die Website eine Police zum Umgang mit Ihren Daten (privacy policy). In der Police steht, daß die Firma Ihren Namen und Ihre Adresse ausschließlich nutzen wird, um Ihnen die angeforderte Broschüre und die Coupons zuzuschicken.

❑ An meiner Reaktion würde sich nichts ändern
❑ Ich würde die verlangte Information eher eingeben
❑ Ich würde weniger gewillt sein, die verlangte Information einzugeben

Wie würde sich Ihr Verhalten in ***Szenario 3*** ändern, enthielte die Website nicht nur eine Privacy Police, sondern außerdem noch das Gütesiegel einer anerkannten Organisation, wie z.B. dem TÜV, die für die Vertrauenswürdigkeit der Website garantiert?

❑ An meiner Reaktion würde sich nichts ändern
❑ Ich würde die verlangte Information eher eingeben
❑ Ich würde weniger gewillt sein, die verlangte Information einzugeben

Wie würden Sie Ihr Verhalten in ***Szenario 3*** ändern, gäbe es ein Gesetz, welches dem Betreiber der WWW Seite verbietet, Ihren Namen und Ihre Adresse für einen anderen Zweck als Ihre Anfrage einzusetzen.

❑ An meiner Reaktion würde sich nichts ändern
❑ Ich würde die verlangte Information eher eingeben
❑ Ich würde weniger gewillt sein, die verlangte Information einzugeben

Wie würde sich Ihr Verhalten in ***Szenario 3*** ändern, enthielte die Website eine Privacy Police, die Ihnen erklärt, daß die Firma Ihren Namen und Ihre Adresse nicht nur dafür nutzen möchte, Ihnen die angeforderte Broschüre und die Coupons zuzuschicken, sondern auch, um Ihnen in Zukunft regelmäßig Neuigkeiten zu ihren Produkten zukommen zu lassen. Ferner plant die Firma Ihre Daten auch anderen Unternehmen zur Verfügung zu stellen, die Produkte verkaufen, für die Sie sich eventuell auch interessieren könnten.

❑ An meiner Reaktion würde sich nichts ändern
❑ Ich würde die verlangte Information eher eingeben
❑ Ich würde weniger gewillt sein, die verlangte Information einzugeben

Vor dem Hintergrund von ***Frage 15***: Wären Sie eher bereit, die Information einzugeben, wenn die Website Ihnen die Möglichkeit geben würde, auf Wunsch von ihrer Mailinglist jederzeit wieder entfernt zu werden?

❑ ja
❑ nein

2. (INDEX SCENARIO 4)

Szenario 4: Sie besuchen eine Website, die Nachrichten, Wetter und Sportergebnisse bereitstellt. Die Seite sieht so aus, als würden Sie sie gerne häufiger besuchen. Die Website fordert Sie auf, Ihre Postleitzahl anzugeben sowie einige Fragen zu Ihren Interessen zu beantworten, damit die Interaktion mit der Website in Zukunft auf Sie persönlich zugeschnitten werden kann. Die Privacy Police der Website erklärt, daß alle Informationen, die Sie angeben sowie Ihr Suchverhalten auf der Website registriert werden. Beides wird genutzt, um die Seiten auf Sie ‚zuzuschneiden' und um die Seite insgesamt zu erhalten und zu verbessern. Gewährleistet ist, daß Ihr Name nie mit diesen Informationen assoziiert wird. Wie würden Sie voraussichtlich reagieren?

❑ Ich würde die verlangte Information eingeben
❑ Ich würde die verlangte Information nicht eingeben
❑ Ich würde die verlangte Information vielleicht eingeben, aber wahrscheinlich würde ich lügen

Wie würdest Du in ***Szenario 4*** reagieren, wenn die Website Sie außerdem nach einigen Informationen über Ihren Computer fragt, damit die Seite besser auf Sie zugeschnitten werden kann. Die Fragen könnten Informationen zu dem von Ihnen genutzten Betriebssystem, dem Browser, dem Monitor oder Modem enthalten.

❑ An meiner Reaktion würde sich nichts ändern
❑ Ich würde die verlangte Information eher eingeben
❑ Ich würde weniger gewillt sein, die verlangte Information einzugeben
❑ Ich würde die verlangte Information vielleicht eingeben, aber wahrscheinlich würde ich lügen

Wie würden Sie in ***Szenario 4*** reagieren, wenn die Website von Ihnen demographische oder soziographische Informationen abfragt, eingeschlossen Ihr Alter, Ihr Geschlecht und Ihr Familieneinkommen?

❑ An meiner Reaktion würde sich nichts ändern
❑ Ich würde die verlangte Information eher eingeben
❑ Ich würde weniger gewillt sein, die verlangte Information einzugeben
❑ Ich würde die verlangte Information vielleicht eingeben, aber wahrscheinlich würde ich lügen

Wie würden Sie in ***Szenario 4*** reagieren, wenn die Website Ihren Namen abfragt?

❑ An meiner Reaktion würde sich nichts ändern
❑ Ich würde die verlangte Information eher eingeben
❑ Ich würde weniger gewillt sein, die verlangte Information einzugeben
❑ Ich würde die verlangte Information vielleicht eingeben, aber wahrscheinlich würde ich lügen

Wie würden Sie in ***Szenario 4*** reagieren, wenn die Website Ihren Namen wissen möchte, ihre Privacy Police jedoch aussagt, daß wenn Sie die Website über 3 Monate nicht besuchen, Ihr Name und alle Informationen gelöscht werden, die man über Sie gesammelt hat.

❑ An meiner Reaktion würde sich nichts ändern
❑ Ich würde die verlangte Information eher eingeben
❑ Ich würde weniger gewillt sein, die verlangte Information einzugeben
❑ Ich würde die verlangte Information vielleicht eingeben, aber wahrscheinlich würde ich lügen

4. NAME

Beim Besuch von Websites, die Informationen über User sammeln, besteht bei vielen Leuten die Haltung, daß sie einige Informationen grundsätzlich bedenkenlos herausgeben, während sie andere Informationen nur unter besonderen Umständen von sich preisgeben. Wieder andere Informationen würden sie nur sehr ungern oder nie auf einer Website hinterlassen. Bitte sagen Sie uns, wie wohl Sie sich dabei fühlen, die folgenden Informationen auf einer Website anzugeben.

Ihren Vor- und Nachnamen

- ❑ Ich würde mich *immer* wohl fühlen, diese Information auf einer Website anzugeben.
- ❑ Ich würde mich *normalerweise* wohl fühlen, diese Information auf einer Website anzugeben.
- ❑ Ich würde mich *manchmal* wohl fühlen, diese Information auf einer Website anzugeben.
- ❑ Ich würde mich *selten* wohl fühlen, diese Information auf einer Website anzugeben.
- ❑ Ich würde mich *nie* wohl fühlen, diese Information auf einer Website anzugeben.

5. ADDRESS

Ihre Postanschrift

- ❑ Ich würde mich *immer* wohl fühlen, diese Information auf einer Website anzugeben.
- ❑ Ich würde mich *normalerweise* wohl fühlen, diese Information auf einer Website anzugeben.
- ❑ Ich würde mich *manchmal* wohl fühlen, diese Information auf einer Website anzugeben.
- ❑ Ich würde mich *selten* wohl fühlen, diese Information auf einer Website anzugeben.
- ❑ Ich würde mich *nie* wohl fühlen, diese Information auf einer Website anzugeben.

6. EMAIL ADDRESS

Ihre e-mail Adresse

- ❑ Ich würde mich *immer* wohl fühlen, diese Information auf einer Website anzugeben.
- ❑ Ich würde mich *normalerweise* wohl fühlen, diese Information auf einer Website anzugeben.
- ❑ Ich würde mich *manchmal* wohl fühlen, diese Information auf einer Website anzugeben.
- ❑ Ich würde mich *selten* wohl fühlen, diese Information auf einer Website anzugeben.
- ❑Ich würde mich *nie* wohl fühlen, diese Information auf einer Website anzugeben.

7. PHONE NUMBER

Ihre Telefonnummer

- ❑ Ich würde mich *immer* wohl fühlen, diese Information auf einer Website anzugeben.
- ❑ Ich würde mich *normalerweise* wohl fühlen, diese Information auf einer Website anzugeben.
- ❑ Ich würde mich *manchmal* wohl fühlen, diese Information auf einer Website anzugeben.
- ❑ Ich würde mich *selten* wohl fühlen, diese Information auf einer Website anzugeben.
- ❑ Ich würde mich *nie* wohl fühlen, diese Information auf einer Website anzugeben.

8. COMPUTER

Informationen über Ihren Computer, Hardware und Software

❑ Ich würde mich *immer* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *normalerweise* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *manchmal* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *selten* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *nie* wohl fühlen, diese Information auf einer Website anzugeben.

9. SALARY

Ihr jährliches Haushaltseinkommen

❑ Ich würde mich *immer* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *normalerweise* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *manchmal* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *selten* wohl fühlen, diese Information auf einer Website anzugeben.+
❑ Ich würde mich *nie* wohl fühlen, diese Information auf einer Website anzugeben.

10. CREDIT CARD NUMBER

Ihre Kreditkartennummer

❑ Ich würde mich *immer* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *normalerweise* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *manchmal* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *selten* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *nie* wohl fühlen, diese Information auf einer Website anzugeben.

11. HOBBY AND INTEREST

Informationen über Ihre Hobbies

❑ Ich würde mich *immer* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *normalerweise* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *manchmal* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *selten* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *nie* wohl fühlen, diese Information auf einer Website anzugeben.

12. HEALTNEW

Informationen über Ihre Gesundheit und Krankheitsgeschichte

❑ Ich würde mich *immer* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *normalerweise* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *manchmal* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *selten* wohl fühlen, diese Information auf einer Website anzugeben.
❑ Ich würde mich *nie* wohl fühlen, diese Information auf einer Website anzugeben.

13. AGENEW

Ihr Alter

- ❑ Ich würde mich *immer* wohl fühlen, diese Information auf einer Website anzugeben.
- ❑ Ich würde mich *normalerweise* wohl fühlen, diese Information auf einer Website anzugeben.
- ❑ Ich würde mich *manchmal* wohl fühlen, diese Information auf einer Website anzugeben.
- ❑ Ich würde mich *selten* wohl fühlen, diese Information auf einer Website anzugeben.
- ❑ Ich würde mich *nie* wohl fühlen, diese Information auf einer Website anzugeben.

C5: Agglomorative Clustering Table

Average Linkage Hierarchical Clustering (cameras and jackets)

Case Processing Summary

Cases					
Valid		Missing		Total	
N	Percent	N	Percent	N	Percent
171	97.7	4	2.3	175	100.0

a Squared Euclidean Distance used

b Average Linkage (Between Groups)

Agglomeration schedule

Stage	Cluster Combined: Cluster 1	Cluster Combined: Cluster 2	Coefficients	Stage Cluster First Appears: Cluster 1	Stage Cluster First Appears: Cluster 2	Next Stage
1	94	206	1.979	0	0	37
2	66	185	2.633	0	0	23
3	6	111	2.654	0	0	19
4	71	196	3.029	0	0	45
5	102	134	3.240	0	0	29
6	184	226	3.672	0	0	8
7	46	79	3.717	0	0	48
8	184	186	4.213	6	0	39
9	193	234	4.251	0	0	45
10	15	40	4.433	0	0	121
11	76	131	4.461	0	0	71
12	51	117	4.564	0	0	48
13	92	221	4.620	0	0	49
14	212	222	4.697	0	0	58
15	121	127	4.795	0	0	80
16	50	231	4.829	0	0	103
17	85	138	4.883	0	0	96
18	14	189	4.892	0	0	22
19	6	59	5.191	3	0	30
20	9	194	5.306	0	0	39
21	84	135	5.402	0	0	84
22	14	235	5.450	18	0	55
23	65	66	5.589	0	2	29
24	47	195	5.709	0	0	47
25	32	62	5.751	0	0	116

26	44	211	5.756	0	0	86
27	36	133	5.805	0	0	42
28	42	199	5.908	0	0	62
29	65	102	6.188	23	5	55
30	6	240	6.283	19	0	56
31	54	208	6.294	0	0	88
32	29	77	6.362	0	0	91
33	89	118	6.413	0	0	157
34	113	223	6.420	0	0	85
35	10	41	6.463	0	0	85
36	128	220	6.465	0	0	78
37	94	110	6.477	1	0	104
38	4	61	6.479	0	0	110
39	9	184	6.527	20	8	70
40	35	104	6.534	0	0	94
41	11	237	6.549	0	0	113
42	36	108	6.641	27	0	97
43	2	87	6.647	0	0	57
44	8	90	6.746	0	0	69
45	71	193	6.862	4	9	93
46	22	101	6.881	0	0	112
47	47	188	6.885	24	0	82
48	46	51	6.913	7	12	87
49	7	92	7.034	0	13	81
50	20	55	7.290	0	0	129
51	27	232	7.374	0	0	86
52	18	45	7.395	0	0	114
53	43	99	7.426	0	0	76
54	100	136	7.475	0	0	77
55	14	65	7.709	22	29	88
56	6	216	7.756	30	0	109
57	2	239	7.764	43	0	70
58	33	212	7.849	0	14	89
59	34	58	7.867	0	0	90
60	52	233	7.883	0	0	111
61	129	207	7.935	0	0	120
62	23	42	8.069	0	28	119
63	17	139	8.122	0	0	109
64	38	236	8.123	0	0	112
65	203	218	8.267	0	0	92
66	183	197	8.292	0	0	125
67	1	192	8.296	0	0	101
68	97	137	8.466	0	0	127
69	8	53	8.477	44	0	75
70	2	9	8.564	57	39	89
71	76	88	8.600	11	0	98

72	26	132	8.625	0	0	142
73	16	28	8.660	0	0	106
74	73	215	8.668	0	0	95
75	8	83	8.862	69	0	120
76	43	122	8.964	53	0	139
77	100	225	9.085	54	0	102
78	106	128	9.099	0	36	105
79	48	120	9.224	0	0	155
80	31	121	9.278	0	15	100
81	7	72	9.304	49	0	108
82	47	91	9.365	47	0	115
83	12	200	9.468	0	0	137
84	84	123	9.564	21	0	152
85	10	113	9.631	35	34	103
86	27	44	9.643	51	26	117
87	46	103	9.690	48	0	99
88	14	54	9.738	55	31	107
89	2	33	9.823	70	58	93
90	34	98	10.246	59	0	107
91	29	63	10.252	32	0	101
92	203	205	10.336	65	0	124
93	2	71	10.481	89	45	116
94	21	35	10.493	0	40	113
95	73	229	10.634	74	0	123
96	67	85	10.662	0	17	144
97	36	109	10.704	42	0	151
98	76	82	10.903	71	0	122
99	46	68	11.180	87	0	108
100	31	96	11.209	80	0	154
101	1	29	11.541	67	91	114
102	100	202	11.752	77	0	130
103	10	50	12.005	85	16	140
104	78	94	12.016	0	37	124
105	5	106	12.030	0	78	126
106	16	126	12.034	73	0	121
107	14	34	12.036	88	90	125
108	7	46	12.058	81	99	128
109	6	17	12.178	56	63	118
110	4	116	12.360	38	0	129
111	52	125	12.522	60	0	150
112	22	38	12.552	46	64	145
113	11	21	12.666	41	94	133
114	1	18	12.679	101	52	148
115	47	60	12.940	82	0	118
116	2	32	13.016	93	25	131
117	27	228	13.411	86	0	133

118	6	47	13.572	109	115	136
119	23	264	13.579	62	0	128
120	8	129	13.598	75	61	137
121	15	16	13.976	10	106	130
122	76	140	14.011	98	0	138
123	73	219	14.104	95	0	131
124	78	203	14.202	104	92	135
125	14	183	14.510	107	66	135
126	3	5	14.545	0	105	136
127	97	217	14.551	68	0	146
128	7	23	14.686	108	119	143
129	4	20	14.800	110	50	149
130	15	100	14.954	121	102	140
131	2	73	15.201	116	123	144
132	49	115	15.232	0	0	165
133	11	27	15.302	113	117	141
134	210	214	15.479	0	0	163
135	14	78	15.886	125	124	141
136	3	6	16.302	126	118	143
137	8	12	16.651	120	83	146
138	39	76	17.185	0	122	145
139	43	190	17.238	76	0	155
140	10	15	17.280	103	130	154
141	11	14	17.324	133	135	153
142	26	254	17.642	72	0	149
143	3	7	17.843	136	128	153
144	2	67	17.979	131	96	150
145	22	39	18.133	112	138	151
146	8	97	18.915	137	127	159
147	130	209	18.919	0	0	157
148	1	30	18.975	114	0	162
149	4	26	19.040	129	142	161
150	2	52	19.359	144	111	152
151	22	36	19.398	145	97	160
152	2	84	19.728	150	84	156
153	3	11	19.971	143	141	158
154	10	31	20.025	140	100	156
155	43	48	21.035	139	79	158
156	2	10	21.271	152	154	159
157	89	130	21.331	33	147	162
158	3	43	22.019	153	155	161
159	2	8	22.838	156	146	166
160	22	224	23.981	151	0	164
161	3	4	24.039	158	149	163
162	1	89	24.489	148	157	166
163	3	210	26.181	161	134	164

164	3	22	27.735	163	160	165
165	3	49	28.229	164	132	167
166	1	2	28.497	162	159	167
167	1	3	31.844	166	165	169
168	37	56	43.079	0	0	169
169	1	37	57.659	167	168	170
170	1	112	59.228	169	0	0

C6: Cluster tables, K-means analysis, Camera shoppers

Initial Cluster Centres

	Cluster 1	2	3	4
Z-Wert(INDEX 1)	-.7530	-.4230	.0822	.5618
Z-Wert(INDEX 3)	-.7870	.1864	.1447	.2676
Z-Wert(INDEX 4)	-.2496	-.2971	-.3902	.5284
Z-Wert(CONCERN ON PRIVACY)	-.1315	-.1793	-.1473	.2258
Z-Wert(NAME)	-1.1447	-.4315	.4126	.5417
Z-Wert(ADDRESS)	-1.1217	-.4069	.3580	.5743
Z-Wert(EMAIL USAGE)	-.7703	-.4992	.0120	.6639
Z-Wert(PHONE NUMBER)	-1.1542	-.1811	.3522	.5112
Z-Wert(COMPUTER)	-.5974	.0233	-.5213	.6218
Z-Wert(MONEYNEW)	-1.0439	.4240	-.3432	.5935
Z-Wert(CREDIT CARD NUMBER)	.1117	-1.0819	.2094	.2868
Z-Wert(HOBBY AND INTERESTS)	-.7066	.0246	-.6891	.8149
Z-Wert(HEALTH)	-.8764	.5939	-.4967	.5193
Z-Wert(AGE)	-.7420	-.0198	-.5064	.7205

Iteration History

	Change in Cluster			
Iteration	1	2	3	4
1	.281	.503	.422	.206
2	.000	.000	.000	.000

Final Cluster Centres

	Cluster 1	2	3	4
Z-Wert(INDEX 1)	-.6470	-.7472	.1850	.6132
Z-Wert(INDEX 3)	-.8163	.1962	.1735	.2007
Z-Wert(INDEX 4)	-.3343	-.2759	-.6846	.5269
Z-Wert(CONCERN ON PRIVACY)	-.2124	-.3106	-.0101	.1517
Z-Wert(NAME)	-1.0424	-.5599	.3563	.4757
Z-Wert(ADDRESS)	-1.0488	-.6046	.4411	.4654
Z-Wert(EMAIL USAGE)	-.8038	-.4687	.0674	.6202
Z-Wert(PHONE NUMBER)	-1.2049	-.1855	.2831	.4606
Z-Wert(COMPUTER)	-.7552	.0447	-.5905	.6549
Z-Wert(MONEYNEW)	-1.0210	.3327	-.5319	.6411
Z-Wert(CREDIT CARD NUMBER)	.1999	-.8702	.2439	.2549
Z-Wert(HOBBY AND INTERESTS)	-.6917	-.0607	-.7215	.8267
Z-Wert(HEALTH)	-.8612	.5978	-.4953	.4536
Z-Wert(AGE)	-.7509	-.1307	-.5374	.7302

Number of Cases in each Cluster

Cluster	1	30.000
	2	21.000
	3	30.000
	4	48.000
Valid		129.000
Missing		42.000

C7:Cluster tables, K-means analysis, Jacket shoppers

Initial Cluster Centers

	Cluster 1	2	3	4
Z-Wert(INDEX 1)	-.7530	-.4230	.0822	.5618
Z-Wert(INDEX 3)	-.7870	.1864	.1447	.2676
Z-Wert(INDEX 4)	-.2496	-.2971	-.3902	.5284
Z-Wert(CONCERN ON PRIVACY)	-.1315	-.1793	-.1473	.2258
Z-Wert(NAME)	-1.1447	-.4315	.4126	.5417
Z-Wert(ADDRESS)	-1.1217	-.4069	.3580	.5743
Z-Wert(EMAIL USAGE)	-.7703	-.4992	.0120	.6639
Z-Wert(PHONE NUMBER)	-1.1542	-.1811	.3522	.5112
Z-Wert(COMPUTER)	-.5974	.0233	-.5213	.6218
Z-Wert(MONEYNEW)	-1.0439	.4240	-.3432	.5935
Z-Wert(CREDIT CARD NUMBER)	.1117	-1.0819	.2094	.2868
Z-Wert(HOBBY AND INTERESTS)	-.7066	.0246	-.6891	.8149
Z-Wert(HEALTH)	-.8764	.5939	-.4967	.5193
Z-Wert(AGE)	-.7420	-.0198	-.5064	.7205

Iteration History

Iteration	Change in Cluster Centers 1	2	3	4
1	1.159	1.801	.898	.598
2	.000	.000	.300	.197
3	.000	.000	.000	.000

Final Cluster Centers

	Cluster 1	2	3	4
Z-Wert(INDEX 1)	-.5822	-.6905	-.3464	.3918
Z-Wert(INDEX 3)	-.4516	-.1761	-.3342	.2500
Z-Wert(INDEX 4)	-.6986	.3446	-.0664	.5159
Z-Wert(CONCERN ON PRIVACY)	-.0075	-.8214	-.2705	.2723
Z-Wert(NAME)	-.7426	-.5180	.3715	.2669
Z-Wert(ADDRESS)	-.8040	-.4317	.2849	.2307
Z-Wert(EMAIL USAGE)	-.6629	-.9254	.1141	.6712
Z-Wert(PHONE NUMBER)	-1.0823	.0000	.6494	.5730
Z-Wert(COMPUTER)	-.4845	-.9104	-.4623	.8748
Z-Wert(MONEYNEW)	-.5343	.2950	.1030	.4363
Z-Wert(CREDIT CARD NUMBER)	-.4300	-1.2150	.1134	.4650
Z-Wert(HOBBY AND INTERESTS)	-.6798	-.3210	-.5183	.9560
Z-Wert(HEALTH)	-.6750	.6312	-.1204	.7482
Z-Wert(AGE)	-.4283	-1.0032	-.3708	.7948

Number of Cases in each Cluster

Cluster	1	11.000
	2	4.000
	3	10.000
	4	17.000
Valid		42.000
Missing		129.000

C8: Cluster tables of K-means analysis all products

Table C8: Cluster tables, K-means analysis, Camera & Jacket shoppers

Initial Cluster Centers

Variables	Cluster			
	1	2	3	4
Z-Wert(INDEX 1)	-.7530	-.4230	.0822	.5618
Z-Wert(INDEX 3)	-.7870	.1864	.1447	.2676
Z-Wert(INDEX 4)	-.2496	-.2971	-.3902	.5284
Z-Wert(CONCERN ON PRIVACY)	-.1315	-.1793	-.1473	.2258
Z-Wert(NAME)	-1.1447	-.4315	.4126	.5417
Z-Wert(ADDRESS)	-1.1217	-.4069	.3580	.5743
Z-Wert(EMAIL USAGE)	-.7703	-.4992	.0120	.6639
Z-Wert(PHONE NUMBER)	-1.1542	-.1811	.3522	.5112
Z-Wert(COMPUTER)	-.5974	.0233	-.5213	.6218
Z-Wert(MONEYNEW)	-1.0439	.4240	-.3432	.5935
Z-Wert(CREDIT CARD NUMBER)	.1117	-1.0819	.2094	.2868
Z-Wert(HOBBY AND INTERESTS)	-.7066	.0246	-.6891	.8149
Z-Wert(HEALTH)	-.8764	.5939	-.4967	.5193
Z-Wert(AGE)	-.7420	-.0198	-.5064	.7205

Iteration History

	Change in Cluster Centers			
Iteration	1	2	3	4
1	.402	.534	.227	.212
2	6.937E-02	.165	.000	5.399E-02
3	.000	.000	.000	.000

Final Cluster Centers

	Cluster			
	1	2	3	4
Z-Wert(INDEX 1)	-.6358	-.7402	.0476	.5986
Z-Wert(INDEX 3)	-.7125	.1060	.0867	.2380
Z-Wert(INDEX 4)	-.4303	-.1145	-.4898	.5259
Z-Wert(CONCERN ON PRIVACY)	-.1580	-.3589	-.0661	.2062
Z-Wert(NAME)	-.9566	-.5794	.3534	.4806
Z-Wert(ADDRESS)	-.9865	-.6028	.4109	.4517
Z-Wert(EMAIL USAGE)	-.7649	-.3957	.0742	.6417
Z-Wert(PHONE NUMBER)	-1.1736	-.1784	.3906	.5204
Z-Wert(COMPUTER)	-.6835	-.0031	-.5431	.7023
Z-Wert(MONEYNEW)	-.8993	.2859	-.3773	.6227
Z-Wert(CREDIT CARD NUMBER)	.0353	-.7898	.2290	.2967
Z-Wert(HOBBY AND INTERESTS)	-.6763	.0095	-.6540	.8871
Z-Wert(HEALTH)	-.8081	.6265	-.3880	.5355
Z-Wert(AGE)	-.6535	-.2286	-.4468	.7775

Number of Cases in each Cluster

Cluster	1	42.000
	2	45.000
	3	34.000
	4	50.000
Valid		171.000
Missing		4.000

D1 to D7 – MAJOR SPSS OUTPUT FILES

Table D1: Demographics of Participants (referred to in section 3.2.)

a)

Occupation (0 = student; 1 through 8 = different jobs)

		Häufigkeit	Prozent	Gültige Prozente	Kumulierte Prozente
Gültig	,00	191	92,7	92,7	92,7
	1,00	5	2,4	2,4	95,1
	2,00	1	,5	,5	95,6
	3,00	1	,5	,5	96,1
	4,00	2	1,0	1,0	97,1
	5,00	2	1,0	1,0	98,1
	6,00	1	,5	,5	98,5
	7,00	2	1,0	1,0	99,5
	8,00	1	,5	,5	100,0
	Gesamt	206	100,0	100,0	

b)

Sex (0 = male; 1 = female)

		Häufigkeit	Prozent	Gültige Prozente	Kumulierte Prozente
Gültig	,00	115	55,8	55,8	55,8
	1,00	91	44,2	44,2	100,0
	Gesamt	206	100,0	100,0	

c)

Internet Use (1 = regularly used; 4 = never used)

		Häufigkeit	Prozent	Gültige Prozente	Kumulierte Prozente
Gültig	1,00	189	91,7	91,7	91,7
	2,00	12	5,8	5,8	97,6
	3,00	2	1,0	1,0	98,5
	4,00	3	1,5	1,5	100,0
	Gesamt	206	100,0	100,0	

d)

Online Purchase (5 = never; 1 through 4 = bought already online)

		Häufigkeit	Prozent	Gültige Prozente	Kumulierte Prozente
Gültig	1,00	35	17,0	17,0	17,0
	2,00	21	10,2	10,2	27,2
	3,00	13	6,3	6,3	33,5
	4,00	47	22,8	22,8	56,3
	5,00	90	43,7	43,7	100,0
	Gesamt	206	100,0	100,0	

Table D2: Correlations between Risk & Satisfaction with Agent Luci (referred to in section 4.5.)

Bivariate correlation between risk perceived before shopping (RIRSK_EMP) and satisfaction with the agent Luci in general (S_A=F1A) as well as satisfaction with the agent's recommendation quality (S_R=F2)

Korrelationen

		RISK_EMP	F1A	F2
RISK_EMP	Korrelation nach Pearson	1,000	-,069	-,060
	Signifikanz (2-seitig)	,	,411	,475
	N	143	143	143
F1A	Korrelation nach Pearson	-,069	1,000	,461**
	Signifikanz (2-seitig)	,411	,	,000
	N	143	146	146
F2	Korrelation nach Pearson	-,060	,461**	1,000
	Signifikanz (2-seitig)	,475	,000	,
	N	143	146	146

**. Die Korrelation ist auf dem Niveau von 0,01 (2-seitig) signifikant.

Table D3: Satisfaction with Agent Luci and Impact on Search (referred to in section 5.1.1.)

a) Accuracy of agent Luci's recommendations was measured on a 5-point scale (1 = not at all accurate; 2 = not really accurate; 3= accurate; 4 = quite accurate; 5 = very accurate)

Perception of Agent Accuracy

		Häufigke	Prozen	Gültig Prozent	Kumuliert Prozent
Gülti	1	6	3,1	3,1	3,1
	2	36	18,8	18,8	21,9
	3	79	41,1	41,1	63,0
	4	56	29,2	29,2	92,2
	5	15	7,8	7,8	100,0
	Gesam	192	100,0	100,0	

b) Distinction of two agent perception groups (group 1 = participants satisfied with Luci's recommendations; group2 = participants not fond of Luci's recommendations)

2 Agent Perception Groups (F2_GR)

		Häufigke	Prozen	Gültig Prozent	Kumuliert Prozent
Gülti	1,00	150	78,1	78,1	78,1
	2,00	42	21,9	21,9	100,0
	Gesam	192	100,0	100,0	

c) Test of Impact that Perception of Agent has on Number of Page Requests

Ränge

	F2_GR	N	Mittlerer Rang	Rangsumme
WEGLÄNGE	1,00	154	93,59	14412,50
	2,00	44	120,19	5288,50
	Gesamt	198		

Statistik für Test[a]

	WEGLÄNGE
Mann-Whitney-U	2477,500
Wilcoxon-W	14412,500
Z	-2,716
Asymptotische Signifikanz (2-seitig)	,007

a. Gruppenvariable: F2_GR

Table D4: Time cost and Impact on Search (referred to in section 5.1.1.)

a) Time cost was measured on a 9-point scale asking participants whether they would have rather done something else instead of shopping in our experimental store (1 = yes, for sure; 9 = not at all)

Perceived Time Cost (F10C)

		Häufigke	Prozen	Gültig Prozent	Kumuliert Prozent
Gülti	1	5	3,2	3,3	3,3
	2	1	,6	,7	3,9
	3	6	3,9	3,9	7,8
	4	9	5,8	5,9	13,7
	5	20	13,0	13,1	26,8
	6	20	13,0	13,1	39,9
	7	31	20,1	20,3	60,1
	8	34	22,1	22,2	82,4
	9	27	17,5	17,6	100,0
	Gesam	153	99,4	100,0	
Fehlen	-999	1	,6		
Gesam		154	100,0		

b) Test of Impact that Perceived Time Cost had on Number of Page Requests

Statistik für Test[a]

	WEGLÄNGE
Mann-Whitney-U	407,500
Wilcoxon-W	11433,500
Z	-,341
Asymptotische Signifikanz (2-seitig)	,733

a. Gruppenvariable: F10C_GR

c) Test of Impact that Perceived Time Cost had on Time spent in the Store

Test bei unabhängigen Stichproben

		Levene-Test der Varianzgleichheit		T-Test für die Mittelwertgleichheit						
									95% Konfidenzintervall der Differenz	
		F	Signifikanz	T	df	Sig. (2-seitig)	Mittlere Differenz	Standardfehler der Differenz	Untere	Obere
ZEITGS_B	Varianzen sind gleich	1,776	,185	,144	144	,886	31,7905	220,5978	-404,2376	467,8185
	Varianzen sind nicht gleich			,109	5,237	,917	31,7905	291,5366	-707,5541	771,1350

Table D5: Satisfaction with Agent Luci in the 2 Store Versions (referred to in section 5.1.2.)

Rangs (product groups: 1= camera; 2 = jackets)

	PROD_N	N	Mittlerer	Rangsum
LUC	1,00	119	74,87	8909,5
	2,00	31	77,92	2415,5
	Gesam	150		

Statistik für Test[a]

	LUCI
Mann-Whitney-U	1769,500
Wilcoxon-W	8909,500
Z	-,353
Asymptotische Signifikanz (2-seitig)	,724

a. Gruppenvariable: PROD_NO

Table D6: Perceived Legitimacy and Importance of Agent Questions in the 2 Store Versions (referred to in section 5.1.2.)

a) Mann-Whitney-U Test on perceived legitimacy of agent questions

Ränge

	PROD_NO	N	Mittlerer Rang	Rangsumme
LEG_M	1,00	56	59,16	3313,00
	2,00	56	53,84	3015,00
	Gesamt	112		

Statistik für Test[a]

	LEG_M
Mann-Whitney-U	1419,000
Wilcoxon-W	3015,000
Z	-,867
Asymptotische Signifikanz (2-seitig)	,386

a. Gruppenvariable: PROD_NO

b) T-Test on perceived importance of agent questions

Gruppenstatistiken

	PROD_NO	N	Mittelwert	Standardabweichung	Standardfehler des Mittelwertes
WICH_M	1,00	56	5,3996	2,4802	,3314
	2,00	56	5,0357	2,6036	,3479

Test bei unabhängigen Stichproben

		Levene-Test der Varianzgleichheit		T-Test für die Mittelwertgleichheit						
									95% Konfidenzintervall der Differenz	
		F	Signifikanz	T	df	Sig. (2-seitig)	Mittlere Differenz	Standardfehler der Differenz	Untere	Obere
WICH_M	Varianzen sind gleich	,577	,449	,757	110	,450	,3639	,4805	-,5883	1,3162
	Varianzen sind nicht gleich			,757	109,742	,450	,3639	,4805	-,5884	1,3162

Table D7: Correlations between Purchase Risk and Uncertainty attached to Jackets and Cameras (referred to in section 5.2.)

Risk has been measured as OPR, reported in section 4.3.1.2.. Uncertainty (Q1, Q2) has been measured as can be seen from table 6 in section 5.2.

Correlations

		RIKS_E	S63	S65A
RIKS_E	Korrelation nach	1,000	-,218**	-,198*
	Signifikanz (2-	,	,008	,016
	N	149	149	149
Q1	Korrelation nach	-,218**	1,000	,479**
	Signifikanz (2-	,008	,	,000
	N	149	150	150
Q2	Korrelation nach	-,198*	,479**	1,000
	Signifikanz (2-	,016	,000	,
	N	149	150	150

**. Die Korrelation ist auf dem Niveau von 0,01 (2-seitig)

*. Die Korrelation ist auf dem Niveau von 0,05 (2-seitig)

Empfangene Unterstützung und Hilfe durch Kollegen:

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- Jens Großklags hat eine Diplomarbeit zu den in Kapitel 6.3. vorgestellten Analysen erarbeitet und bei der Aufbereitung des Zahlenmaterials geholfen.
- In Kapitel 5 sind Kommentare eines ‚Double-Peer-Review' – Prozesses eingegangen, und zwar durch Gutachter der Konferenz: HICSS, Haswaii International Conference on System Sciences
- In Kapitel 6.2. sind Kommentare eines ‚Double-Peer-Review' – Prozesses eingegangen, und zwar durch Gutachter der Konferenz: 14th Bled Electronic Commerce Conference
- In Kapitel 6.3. sind Kommentare eines ‚Double-Peer-Review' – Prozesses eingegangen, und zwar durch Gutachter der Konferenz: ACM EC'01, Conference on Electronic Commerce

„Ich bezeuge durch meine Unterschrift, dass meine Angaben über die bei der Abfassung meiner Dissertation benutzten Hilfsmittel, über die mir zuteil gewordene Hilfe sowie über frühere Begutachtungen meiner Dissertation in jeder Hinsicht der Wahrheit entsprechen."

Berlin, 8. Februar 2002

Sarah Spiekermann

Hiermit erkläre ich, Sarah Spiekermann, dass ich mich bisher noch an keiner Institution einem Doktorexamen unterzogen habe. Ferner wurde die Dissertation bisher an noch keiner anderen Fakultät vorgelegt.

Berlin, den 8. Februar 2002

Sarah Spiekermann