ANTECEDENTS OF THE QUALITY OF ONLINE CUSTOMER INFORMATION

(Completed Paper)

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Abstract: When the concept of Customer Relationship Management emerged in the 1990s, the need for high quality data became of paramount importance in order to adequately address customers. Individualization strategies were developed to improve relationships with existing customers and therefore generate more revenue. In order to fine-tune those strategies, demographic as well as psychographic information and previous buying behavior may be used. However, a lot of resistance against providing personal information on the side of the customers exists, which is evidenced by consciously supplied false information. This paper analyzes some important constructs which can be seen as antecedents for the provision of correct personal data. A research framework is developed and empirically tested with an online survey. The results indicate that the benefits from individualized communication, trust in the secure data submission over the Internet and the degree of information available to customers as to how companies treat personal data, significantly influence users' attitudes toward providing correct information.

Key Words: Data Quality, Information Quality, IC Models, Customer Relationship Management, Online Data Collection, Trust in the IQ Context

INTRODUCTION

In the 1990s the predominant paradigm of Transaction Marketing was challenged by the central assumptions of so-called Relationship Marketing, which focuses on building relationships with customers rather than only concentrating on the amount of transactions being conducted. Although the term Relationship Marketing was coined a couple of years earlier [4], the emergence of new technologies which allow a company to gather, store and analyze data on a large-scale base laid the foundation for the actual feasibility of techniques aimed at targeting one customer at a time [28]. Besides addressing customers by name, sophisticated applications, such as collaborative filtering allow a company to suggest products which may be of potential interest for certain user groups [17]. Clearly, the quality of these recommendations heavily depend on the amount and quality of customer data being available. Demographic data, such as gender or age, may be enhanced by information which can be gained by analyzing previous purchases, purchase intentions and psychographic attributes. While the further effects of data quality on customer relationships depend upon a multitude of factors and need to be empirically validated [13], this paper concentrates on the users' intentions to provide correct data.

For the remainder of this paper we follow the approach of Zahay et al. [35] and differentiate between transactional data and relational data. While the former includes e.g. demographic data and purchase histories, the latter one comprises psychographic attitudes such as values, motivations, beliefs, attitudes and lifestyle [27]. It has to be mentioned that in scholarly literature a variety of different data categorizations which have varying coverage exists. Within the context of individualization Adomavicius and Tuzhilin [1] differentiate between factual data (mainly demographic information) and transactional data. For the purpose of this paper both data types are subsumed under the notion of transactional data as opposed to relational data.

Transactional data usually can be gained comparatively easily when transactions take place online or customer cards are used in the offline world. None the less, the problem remains that the buyer may not correspond to the actual user of a product. In order to avoid distortions of user profiles, companies such as Amazon.com offer the opportunity to wrap a purchase as a present, which can be seen as an indicator that the product might be bought for someone else.

In order to find out about an individual customers' relational data or intended purchases, surveys must be conducted. While some approaches, such as the aforementioned collaborative filtering, base their recommendations on characteristics of user groups, the One-to-One Marketing approach strives to address an individuals' needs as thoroughly as possible, which calls for the gathering of personal data.
A preliminary Web site analysis that included more than 900 Austrian retailers revealed that only few companies use online forms to find out about users' relational data and buying intentions. The same holds true for offline surveys that only on rare occasions include more than the collection of demographic variables. Only in few cases we found Web sites that allowed for an automated notification of prospects if potentially interesting products are available.

The remainder of this paper is structured as follows. As a starting point, a framework depicting several methods of data collection will be presented. By applying the different dimensions of data quality being developed in scholarly literature, we will demonstrate various problematic quality aspects that may occur. Results from a number of empirical studies will demonstrate that the data gathered from surveys may be erroneous due to a number of different reasons. In order to measure the influence of different key constructs on the customers' willingness to provide correct data, a model will be created and evaluated with the help on an online survey. Several hypotheses about antecedents of users' willingness to provide correct data will be tested with the help of the empirical data. Finally, implications for practitioners are discussed and suggestions for further research projects are given.

QUALITY PROBLEMS OF DATA COLLECTION

Figure 1 summarizes the ways in which customer data can be gathered online. While the completion of transactions may act as a primary source of transactional data, surveys may be used to gather relational data and information about intended purchases. However, existing data (both transactional and relational) may be used to predict intended purchases by segmenting user groups and providing them with suitable product offerings.

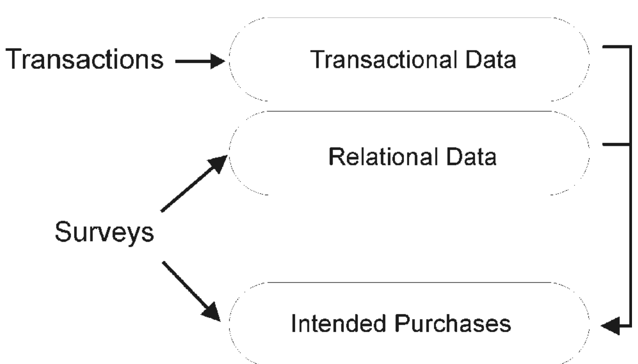

Figure 1: Collection and Generation of Customer Data

By applying the conceptual data quality framework developed by Wang and Strong [33] we intend to reveal potential problems and pitfalls that may come along with the usage of such data. Transactional data usually can be verified by actually completing the transaction. In the case of an online transaction this at least means that certain types of information, such as the e-mail address or the credit card number, must be free of error. In the case of a postal delivery, data such as the delivery address must be at least interpretable. As far as any information collected with the help of surveys is concerned, reliable methods of verification are missing. Due to lack of control during the filling out of the questionnaire, problems pertaining to the accuracy and the objectivity of the data may occur. In addition to that, it may be even unclear who actually filled out the questionnaire, which may be seen as a problem of traceability (a dimension that was originally included into the work of Wang and Strong [33] and later removed due to inconsistent assignment by study participants). In an online survey the only piece of information that can be used for authentication may be an IP address which itself may not be exactly traceable, as is the case when proxy servers are used. While companies may rely upon endorsers, such as non-governmental organizations, professional bodies and opinion leaders to achieve authenticity [11], individuals usually do not explicitly verify their own identity. In many cases they may even be unwilling to do so.

Existing literature on information privacy reveals that users consciously provide wrong data when being asked to key in information online. An online survey, conducted in the United States, found that 82% of a total of 2,468 respondents refused to give information to a Web site because they felt it was too personal or unnecessary. 64% decided not to use or purchase something from a Web site because they were not sure how their personal information would be used, and 34% admitted to having supplied fictitious or false information when they were asked to register [6]. In comparison with these results, Neus [23] reports that even when they are given an incentive, only 22% of the users (the universe being 352 faculty members and students from Bonn and Aachen University) admit to reporting everything truthfully. Being asked for information which a user does not want to reveal, 29% quit, 50% look for an alternative and 21% falsify their answers. By using the data from two biannual surveys (1997 Nielsen Media Research/ CommerceNet Internet Demographics Study and the GVU 7th WWW user survey) Hoffman et al. [14] report that almost 95% of the respondents state that they have at least once declined to provide personal information and 40% have fabricated demographic data. These figures clearly indicate that customer data being gathered on the Internet may neither come up to the desired standard of intrinsic data quality (believability, accuracy, objectivity, reputation) nor to those of representational data quality (interpretability, ease of understanding, representational consistency, concise representation).

Besides having users which consciously provide false data, there are automated tools which parse the source code of Web sites in order to find online forms and fill them with fictitious profiles (e.g. www.superbot.tk). Other tools exist that allow for the automated exchange of cookies, thereby leading the efforts of companies to identify former users ad absurdum (e.g. www.cookiecooker.de).

ONLINE DATA TRANSMISSION

During recent years an increasing number of companies started to individualize their online communication with the intention of strengthening customer relationships. The theoretical background of using individualization strategies in a business context can be traced back to the beginnings of Relationship Marketing [4] and One-to-One Marketing [28]. The Internet may be regarded as the ideal medium that enables the individualization of mass customer communication [21]. With consumers increasingly getting Internet access, many companies realized that large customer data bases and efficient methods of analysis allow them to target consumers according to their individual preferences. As was mentioned above, Interactive Marketing and Data Base Marketing began to replace the concepts of Transaction Marketing [34]. In addition, consumers have to be made aware of the potential benefits which may arise from an individualized communication, such as support with buying decisions and reduced commercial communication due to better targeted marketing strategies.

Hypothesis 1 (H1). *Perceived benefits from individualized communication will positively affect the attitude toward providing correct data.*
In information systems research, a plethora of scholarly literature concerning the importance of trust in the Internet exists. Previous research has found that trust negatively influences perceived risk [26], and positively influences perceived usefulness and the intended use of an online shopping system [9]. Subsequently, trust can be seen as one of the major influencing factors for the success of Internet commerce [31].

Hypothesis 2 (H2). *Trust in secure data transmission will positively affect the attitude toward providing correct data.*
Previous research has shown that perceived behavioral control differentiates between individuals with positive attitudes toward secondary information use and those with negative attitudes [7]. In our study we focus on the users' awareness of how companies handle their personal data, including a certain amount of knowledge about the process of data collection and data storage. In addition to that, we assess the perceived knowledge about applicable legal regulations.

Hypothesis 3 (H3). *Awareness of data usage will positively affect the attitude toward providing correct data.*
Based on the assumption that the awareness of data usage within the company depends upon the perceived knowledge of the data collection process, and the storage and usage of this data, which may be described more generally as trust in data usage, we hypothesize a mutual influence between trust in secure data transmission and awareness of data usage.

Hypothesis 4 (H4). *A positive relationship between trust in secure data transmission and awareness of data usage exists.*
Consumers usually tend to substantially underestimate the number of data bases in which they appear [5]. Given the manifold potentials of personal data for commercial usage and especially for individualizing marketing communication, we assume that a high level of general awareness will lead to a low level of perceived lack of behavioral control.

Hypothesis 5 (H5). *Awareness of data usage will negatively affect perceived lack of behavioral control.*
Considerable amounts of studies which are based on the Theory of Reasoned Action and the Theory of Planned Behavior have empirically validated the positive influence of attitude on behavioral intention [18], [30], [10]. We therefore assume that the general attitude toward providing personal data on the Internet will have a significantly positive influence on the Internet users' intentions toward providing correct data.

Hypothesis 6 (H6). *The attitude toward providing correct data will positively affect behavioral intention.*
Besides being influenced by the users' attitudes, the behavioral intention (i.e. the willingness to provide correct data) also depends upon the perceived behavioral control. We hypothesize that users which perceive a lack of behavioral control will tend not to provide personal data over the Internet.

Hypothesis 7 (H7). *The perceived lack of behavioral control will negatively affect behavioral intention.*

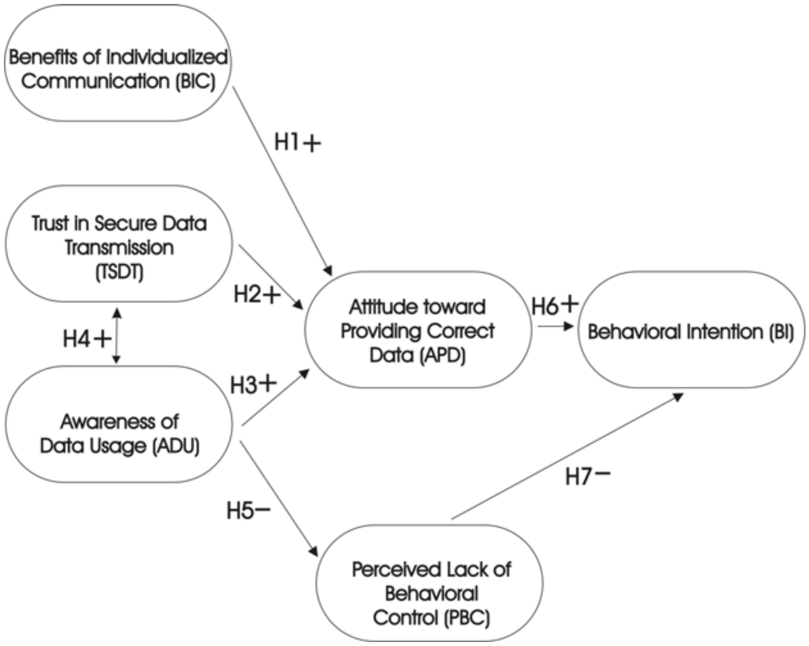

Figure 2: The Research Model

The hypotheses discussed above are summarized in Figure 2 in a concise way. As can be seen, numerous interdependencies between the single constructs exist, which call for a Structural Equation Modeling approach. This allows for a simultaneous estimation of the structural and the measurement models. The following sections deliver some insight how the measurement model was created and discuss the results from the survey.

RESEARCH METHOD

Due to the lack of existing scales that may be used for assessing users' attitudes toward the submission of personal data, new scales had to be developed. This was done by conducting qualitative interviews and using content analysis to generate a pool of items. Subsequently, the scales were tested for reliability and validity. The underlying theoretical background of the model can be found in the Theory of Reasoned Action [3] and the Theory of Planned Behavior [2], which deal with a number of antecedents influencing an individual's intention and actual behavior. Following this stream of research, the Technology Acceptance Model which concentrates on two major constructs, namely 'Perceived Ease of Use' and 'Perceived Usefulness' as antecedents of system usage, has gained widespread acceptance in the Information Systems community [8]. Numerous empirical studies support the basic assumptions of the theories aforementioned and usually added new constructs [30], [9], [25], [19], [18]. The following sections give a short introduction in the process of scale development and depict the results of the user survey. First, some general information about the sample is given, followed by a presentation of the scales used and the research model. We used qualitative pre-studies with 25 experts in order to find the constructs which are important for the intention of providing correct data. The expert sample included scholars, who are conducting research in the field of privacy and consumer behavior, producers of CRM software, CRM consultants, market researchers and representatives from companies trying to build up relationships with their customers. By using methods of qualitative content analysis [20] we came up with a number of constructs and the respective indicators.

USER SURVEY

In order to ensure the understandability of the items a number of pretests were conducted. Since the universe of our research consists of Internet users, an online-survey was carried out. In order to reach a wide range of different users, we posted a link to our survey on the Web site of a large Austrian online portal, which is operated by one of the major telecommunication providers in Austria. We used self-programmed sliders with a range from 1 to 100 to generate a magnitude scale (sometimes called Visual Analogue Scale, Graphical Rating Scale or Continuous Rating Scale) instead of the commonly used Likert scales, thereby avoiding some weaknesses of the latter, e.g. the loss of information due to the limited resolution of the categories [36] or the inadvertent influence of the investigator on the responses by constraining or expanding the response range available to the respondent [32]. Previous research has shown that there are no overall differences between category scales and magnitude scales and that the latter can be considered a valid and reliable alternative, since both methods show considerable degrees of convergent and discriminant validity [22]. Although the loss of information from categorizing an unobserved continuous variable into an ordered categorical scale can be reduced to a minimum when using at least five categories and multi-item scales [29], a magnitude scale appeared to be the best research method available in view of the exploratory nature of our research design and the required eligibility of the data for the subsequent multivariate analyses.

Several precautions were taken in order to avoid consciously falsified responses: besides carefully testing our scales, we decided not to give an incentive of any kind. Furthermore, no personal data was collected which would allow one to discover the actual identity of the respondents. In addition to that, we provided a contact address of the university department to create trust and, finally, a number of statistical tests were conducted to search for outliers and implausible answers.

RESULTS

Demographic characteristics and the frequency of Internet use of the sample can be found in Table 1. A total of 405 Internet users completed the questionnaire, whereat substantially more men (72.1%) than women (26.9%) participated. As far as the age is concerned, most of the respondents (65.4%) were between 20 and 49 years old. 35.1% graduated from high school, 26.2% hold a degree from secondary school, and 15.1% possess a university degree. Most of the respondents work as administrative or technical employees (34.8%), followed by students (13.1%) and civil servants (9.9%). The average Internet usage indicates a quite diverse sample. While 13.8% point out that they use the Internet fewer than five hours a week, 17.5% may be regarded as heavy users with more than 30 hours a week.

Sex		***Occupation***	
Male	72.1%	Executive employee	5.4%
Female	26.9%	Administrative/technical employee	34.8%
Age		Skilled worker	5.7%
- 19 years	5.9%	Civil servant	9.9%
20 – 29 years	24.7%	Blue-collar worker	3.2%
30 – 39 years	23.2%	Self-employed	7.7%
30 – 49 years	17.5%	House-wife or husband	1.7%
36 – 40 years	10%	Retired	7.9%
50+ years	21.2%	Student	13.1%
n/a	7.4%	Unemployed	1.2%
		Other	8.4%
Education		n/a	1.0%
Primary School	2.2%		
Secondary School	26.2%	***Frequency of Internet use***	
High school graduation	35.1%	1- 5h/week	13.8%
Technical College	6.7%	6 – 10 h/week	23.7%
University	15.1%	11 – 20 h/week	29.4%
Other	13.8%	21 – 30 h/week	13.3%
n/a	1.0%	30+ h/week	17.5%
		n/a	2.2%

Table 1: Characteristics of Respondents (n = 405)

Table 2 provides some information about the scales used in this survey. Besides giving descriptive information about the items including the mean, standard deviation and the median, we used Cronbach's alpha (internal consistency reliability coefficient) in order to measure the reliability of the scale. Nunnally [24] suggests a minimum level of .5 to be acceptable for exploratory studies. Two scales ('Trust in Secure Data Transmission' and 'Awareness of Data Usage') fall marginally short of this threshold, while all other scales exhibit a satisfactory level of reliability. As far as the users' general assessment of the individual constructs is concerned (being expressed by the mean and median values), it can be seen that the 'Behavioral Intention' gets the highest level of agreement, closely followed by the 'Perceived Lack of Behavioral Control'.

Item	***Wording***	***Mean***	***S.D.***	***Median***	α
BIC01	Individualized communication supports my buying decisions	46.51	34.02	50	.816
BIC02	Individualized communication increases my satisfaction with the company	54.65	32.15	60	
BIC03	Individualization leads to reduced communication	55.45	31.81	57	
TSDT01	In general, the transfer of data over the Internet is safe	44.68	30.20	50	.438
TSDT02	The perils of the Internet are overestimated	41.70	33.42	35	
ADU01	The usage of data in companies is transparent	30.65	26.77	26	.497
ADU02	I usually know, when my data is collected und which companies store them	36.14	30.96	30	
ADU03	I know the relevant legal regulations concerning the gathering, storage and usage of data	46.72	32.33	50	
	How do you consider it in general to divulge data on the Internet?				
APD01	Bad ... Good	42.06	27.18	50	.899
APD02	Not reasonable ... Reasonable	50.71	27.34	50	
APD03	Useless ... Useful	52.20	26.54	50	
APD04	Negative ... Positive	44.79	25.26	50	
PBC01	Companies will get my data, even if I don't provide them deliberately	78.22	25.16	84	.645
PBC02	On the Internet, I am often coerced to give away data	62.49	31.40	71	
PBC03	Only on rare occasions I can decide on my own whether to give away data or not	57.34	33.21	63	
BI01	I am going to pass on my name on the Internet within the next month	68.19	33.15	77	.846
BI02	I am going to pass on my e-mail-address on the Internet within the next month	73.22	30.75	83	

Table 2: Construct Scales

Structural Equation Modeling (SEM) appears to be the best available statistical technique for testing the hypotheses, since it allows for the simultaneous testing of all the hypotheses formulated above and includes indirect effects of one latent variable on another. The software tool used for all analyses was AMOS 4.0. The data analysis generated a Chi-Square value of 202.501 (df = 111) which leads to a $\chi 2$/df of 1.824. Figure 3 shows the standardized regression coefficients with their relevant p-values. It can be seen that all but one hypotheses (and thus the complete theoretical model) are supported by the data. The assumed negative relationship between the perceived lack of behavioral control and behavioral intention turned out to be negative instead of positive. All coefficients are statistically significant ($p < .05$).

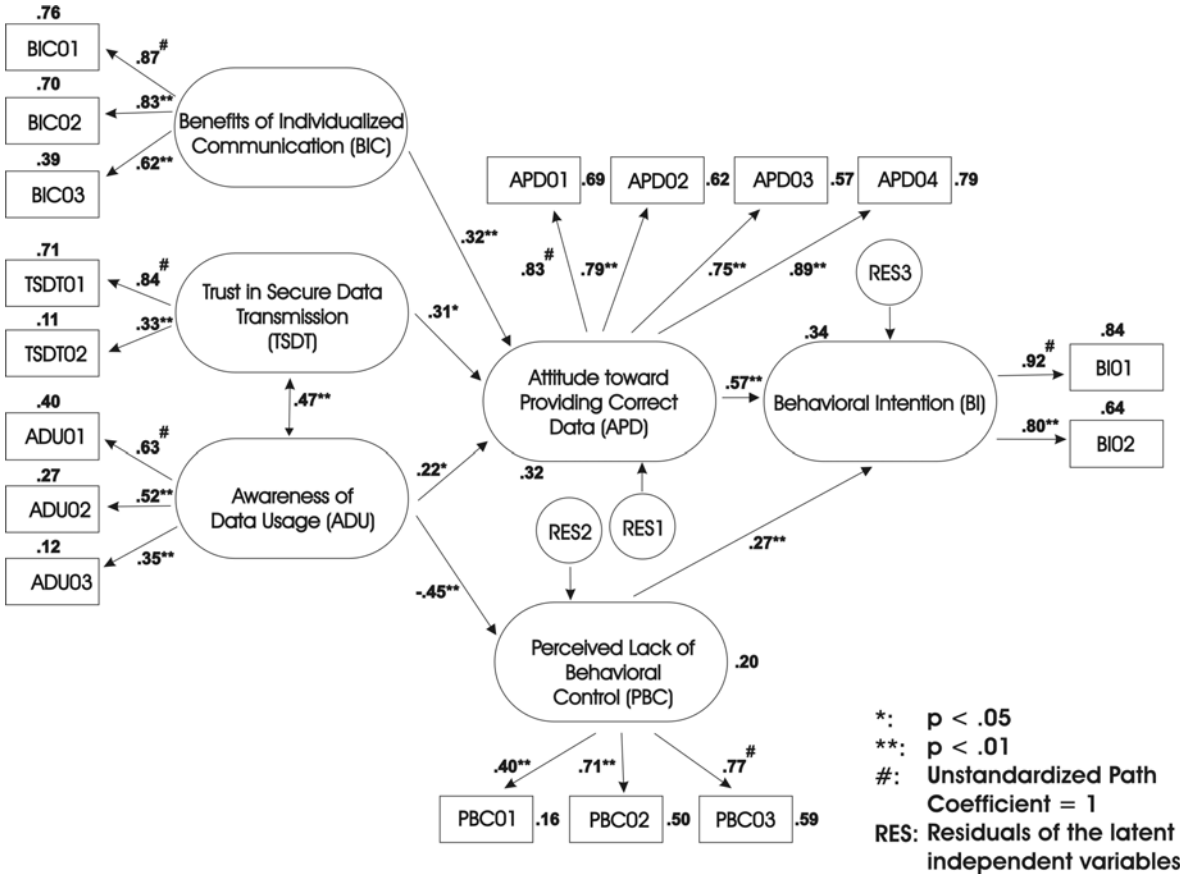

Figure 3: Intention to Give Away Correct Data (n = 405)

The results show a positive relationship between the perceived benefits of individualized communication, the trust in secure data transmission, the awareness of data usage and the users' attitudes toward providing correct data (H1 to H3). Furthermore, there exists a strong correlation between the trust in secure data transmission and the awareness of data usage (H4). As was hypothesized, the awareness of the companies' usage of personal data negatively influences the perceived lack of behavioral control. Both the attitude toward providing correct data (H6) and the perceived lack of behavioral control (H7) exert a positive influence on the behavioral intention to provide correct data, whereby only the first relationship was predicted by the hypothesis. Next to dependent latent variables the squared multiple correlations (SMCs) can be found which represent the proportion of variance that is explained by the predictors. As can be seen in Figure 3, the variances of 'Behavioral Intention', Attitude toward Providing Correct Data' and 'Perceived Lack of Behavioral Control' can be explained by our model to the extent of 34%, 32% and 20%, respectively.

	Goodness of fit measure	*Recommended Value*	*Model Value*
χ^2/df	χ^2/Degrees of Freedom Ratio		1.824
RMSEA	Root Mean Square Error of Approximation	<.06 (15) <.08 (16)	.045
GFI	Goodness of fit index	>.9 (9)	.945
AGFI	Adjusted goodness of fit index	>.8 (9)	.924
NFI	Normed fit index	>.95 (15)	.922
TLI	Tucker-Lewis or nonnormed fit index (NNFI)	>.9 (12)	.954
CFI	Comparative fit index	>.95 (15) >.9 (9)	.963

Table 3: Fit Indices of the Hypothesized Model

The goodness of fit measures of the model are depicted in Table 3. With the exception of the NFI, all indices comply with the recommended standards. As a whole, the indices indicate an adequate fit of the model to the corresponding data.

CONCLUSION AND LIMITATIONS

Individualizing communication is regarded as a prerequisite for building relationships with customers, which in turn should lead to an increase in the overall amount of transactions being conducted. However, any form of communication can only be effective if the recipient is addressed adequately, i.e. personal preferences are taken into account. When dealing with a large amount of anonymous consumers, companies rely heavily on the data being gathered in data bases in order to design their communication process. Given the preeminent importance of the quality of this data (especially relating to accuracy, interpretability, ease of understanding, objectivity, timeliness, completeness and traceability), this paper strives to analyze which antecedents may exert an significant influence on the users' willingness to provide correct data. While some data (e.g. transactional data, such as the address) have to be correct in order to carry out transactions, other data (e.g. personal interests, such as hobbies) are comparatively easy to fake. While previous research has shown that many influencing factors exist which may prevent an individual from providing correct data, there is a lack of empirical research analyzing the antecedents of data transmission. This paper shows that antecedents exist that may shape an individual's attitude toward giving away personal information. In addition to the perceived benefits of individualized communication, the consumers' trust in an appropriate handling of personal data within the organization and, which is especially important in the online world, trust in the secure transmission of the data act as major influencing factors.

From a practitioner's point of view several implications can be drawn:

- First and foremost, the quality of consumer data gathered on the Internet remains unclear unless it can be verified. Previous research has shown that users consciously provide wrong data for a variety of reasons. Therefore, companies should deploy rigid data quality mechanisms before individualizing their communication.
- Users have to clearly understand the benefits of individualized communication. This may either be a reduction of mailings or pieces of information that better suit the interests of the recipient.
- Users are usually reluctant to submit personal information over the Internet. Companies should use secure transmission channels and then call the users' attention to it.
- According to previous research, trust (both in the Internet and the organization collecting the data) turned out to be of outstanding importance. As far as the organization itself is concerned, care has to be taken to make the process of data storage and usage as transparent as possible. While major legal differences between European countries and the United States of America exist, it may be advisable for organizations in both continents to indicate the proposed utilization of the data.

As in most empirical research projects, limitations exist that have to be taken into account when interpreting the results of this survey. First, there may be a non-response bias, since users filled out the questionnaire voluntarily. As described above, great care was taken to ensure the quality of the data. However, there was no way to assess the opinions of those Internet users who decided not to fill out the questionnaire. Second, as far as the scales are concerned further improvement is suggested. While a number of pretests indicate a good level of reliability and validity, further refinement may lead to improved results. Besides working on the scales, future research may concentrate on the individual assessment of the importance of different data types (e.g. address information vs. credit card information) and, from a practitioner's point of view, may concentrate on developing measures to at least control the quality of those data which cannot be unambiguously verified.

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