A NATURAL LANGUAGE TECHNOLOGY-ENHANCED MOBILE SALES ASSISTANT FOR IN-STORE SHOPPING SITUATIONS

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Abstract

Sales talks between customers and sales personnel are efficient and preferred means for exchanging information that is relevant for purchase decisions on non-commodity products. Dialogs used in sales talks are governed by complex and in many respects conflicting intentions on both sides. While previous Decision Support Systems (DSS) are designed by the principle of congruent intentions of communication partners, we present an approach that extends this by congruent and opposing intentions of communication partners. We use a design methodology for dialog-based purchase DSS that use Natural Language Technologies (NLT) for dynamically creating question-answer-based sales dialogs. It is first shown how dialog schemata are obtained by a field study and evaluated by subjects. In the second part, these schemata are integrated in a Natural Language Technology-enhanced Mobile Sales Assistant (NLT-MSA). The role of NLT-MSA is to take the position of a sales person with the task to balance congruent and conflicting intentions during sales dialogs. Results of a lab experiment (n=54) are discussed by which the use of a NLT-MSA prototype in sales situations were tested. As part of this study, test persons rated application domains for NLT-MSA that will guide future field experiments in the large.

Keywords: Dialog-based HCI, decision support system, customer behavior, empirical study, diffusion of innovation, mobile application.

1 Introduction

Sales talks between sales personnel and customers are dialogs between two parties with conflicting goals. From the customer's perspective, a sales talk has the goal to reduce uncertainty and equivocality related to purchase decisions (Daft and Lengel, 1986). Furthermore customers are likely to make informed buying decisions by considering product characteristics (e.g., price, properties, design), alternative products (in-store, online stores, other retailers), and customer and expert reviews (Mudambi and Schuff, 2010). But at the same time, customers tend to reduce their product search efforts (Häubl and Trifts, 2000). By contrast and on the seller side, the goal is to increase profit by various strategies, such as product and price differentiation (Choudhary et al., 2005; Stremersch and Tellis, 2002) and pushing slow-sellers (Gallego and Ryzin, 1994) and perishable goods (Elmaghraby and Keskinocak, 2003).

Following media richness theory, face-to-face dialogs in sales situations can be characterized by four key factors: (1) transmission of multiple cues, (2) immediacy of feedback, (3) language variety, and (4) personal focus (Daft and Lengel, 1986). Thus they provide rich communication that fit very well with purchasing complex, critical, and rarely bought products while commodity products are best supported by lean communication, such as leaflets (ibid.). In contrast to these needs, process optimization and cost cutting lead to unmet customer needs for sales talks. To fill this gap, stores use printed leaflets or sometimes use audiovisual displays located next to products. Hence, needs for rich communication media are replaced by lean communication media and, thus, fail in these cases to reduce customers' uncertainty and equivocality for non-commodity products. Purchase losses and missed opportunities for building customer relationships are the result.

It is a long-standing vision of the Information Systems (IS) community to use Natural Language technologies (NLT) for IS (Storey et al., 2008; Suh and Jenkins, 1992; Vassiliou et al., 1983). In recent years, NLT for language understanding and language generation are becoming mature while NLT support of dialogs is still a challenge. In dialogs one must keep track of what was already said (dialog history), mutual intentions and expertise must be anticipated (context), and culturally framed dialog schemes must be considered (pragmatics). Depending on the type of situation, actors' intentions are similar or even in conflict with each other. Situations of similar intentions are typical for traditional IS, such as Decision Support Systems and Business Intelligence. E-business IS cope with conflicting intentions of sales organizations and customers by adopting a simple strategy. That is, making purchase intentions as explicit as possible with little adaptation to dialogs which contrasts with face-to-face sales dialogs. Instead dialogs are engraved into static web-site designs and navigational patterns.

With NLT sales communication can be strongly adapted to customer communication and other behaviors and, thus, resemble and even enhance human sales talks by leveraging information provided by web sites that, for instance, provide product reviews or product tests. The general research challenge is twofold. First, the abundance of information must be matched with local information needs. Second, relevant information must be dynamically integrated into a sales dialog that is structured with regard to cultural background knowledge. In essence this challenge combines information retrieval with problem-solving in groups. Some initial attempts were made to integrate NLT into sales dialogs of E-Business situations (Kauffman and Walden, 2001). However, support of dialogs and consideration of conflicting intentions are still a key problem.

Physical sales situations for consumer goods resemble online sales situations in various respects but also provide characteristic differences; for example, private versus public environments, willingness to invest more time versus time-limited sales situations, relatively new versus long-term knowledge on sales situations, and high versus low accessible computing power and information access. This means that sales communication in online sales situations characteristically differs from physical sales situations. Today with Internet-enabled mobile devices customers have access to any Internet resource. Moreover, Internet of Things technologies such as Radio-frequency identification (RFID) technologies with object identification by Electronic Product Codes (EPC) or barcode technologies with object identification by European Article Number (EAN), allow customers to map global information with products present in a sales situation (Kowatsch and Maass, 2010; Kowatsch et al., 2011; Pramatari and Theotokis, 2009; Resatsch et al., 2008). On one hand, NLT provides a means for adapting sales-related information to customer needs. On the other hand, NLT supports more natural communication needs of customers.

In the current work, we apply a design science oriented methodology for the development and evaluation of NLT-enhanced mobile sales assistants (MLT-MSA) that are used in in-store shopping situations. The methodology consists of two design cycles (Hevner et al., 2004). In the first one, expert interviews and field studies are conducted to identify and evaluate sales questions relevant to customers in shopping situations. These questions are then analyzed with regard to information requirements that can be executed at run-time for dynamic mapping with various information sources. Hence, this approach is highly flexible with respect to changing information sources. In the second design cycle, a particular NLT-MSA instance is developed and empirically evaluated with regard to adoption research and the information requirements derived from the first design cycle. Hereby, intentions of retailers are considered for the generation of answers provided by the NLT-MSA instance. The contribution of this work is therefore to build and evaluate a prototypical realization of NLT-MSA that informs the design of future NLT-MSA. Thus, for the first time a complete IS design cycle is presented for NLT-based IS.

The rest of this paper is structured as follows. Next, we describe the underlying conceptual IS model, Abstract Information System Model (AISM), and a dedicated IS design method for NLT-MSA. Then, two build-and-evaluate loops for the design of a NLT-MSA are described. And finally, theoretical and practical implications are discussed before a summary is provided.

2 Design Framework and Methodology

IS are compounds of social systems, information spheres, and service systems that use information technology infrastructures for the realization of desired situations (Lamb and Kling, 2003; Orlikowski and Barley, 2001). In extension to IS that only process information objects, design models for IS embedded in physical environments, called Ubiquitous IS (UIS), also require means for representing physical entities. Hence, design models for UIS require conceptual descriptions of physical objects that can be related to one another and to other conceptual elements of the design model.

With the Abstract Information System Model (AISM), we bring together these three conceptual classes for design models of digital IS with the additional dimension for the conceptual class of physical entities: (1) Social system: set of roles available with rights, obligations, and prohibitions, (2) Information sphere: set of information objects used within the realm of a UIS, (3) Physical object system: set of physical entities available within all situations in which a UIS can be used and (4) Service system: set of all digital and physical services available within all situations in which a UIS can be used. Note that AISM is a conceptual, i.e., logical description of an IS and in particular an UIS that can be realized, and thus instantiated, by various infrastructures. For instance, the information sphere can be realized by digital databases or by pen and paper. Hence, information objects are conceptual descriptions that can be realized by digital or any other kind of content objects.

In this work, the Social System is modeled as a one-to-one in-store shopping situation, i.e. a single sales person and a single customer. From the information sphere, various product-related information resources are provided. The sales service is realized by one particular NLT-MSA instance.

Consistent with prior work (Hevner et al., 2004), we first apply a design-cycle that addresses Information Sphere and Social System. Hereby, we focus on product information that is relevant to a customer in an in-store shopping situation. That is, to identify questions which arise from a customer's perspective when making a purchase decision. Based on a corpus of sales talks from a customer electronics fair, questions were extracted and evaluated against their compatibility with an in-store shopping situation (Rogers, 2003).

Then, in the second design cycle, we develop and evaluate a NLT-MSA from a customer perspective based on the findings of the first design cycle. This step covers the Social System, Service System and Physical Object System of AISM. But this step is also used to cross check the results from the first design cycle. Furthermore, retailer intentions are integrated in the NLT-MSA in this step. The NLT-MSA was developed as domain-specific dialog system that uses a Natural Language Processing (NLP) approach consisting of text schemata and planning technologies supported by a semantic knowledge base. For the evaluation, IT adoption constructs are used (cf. Kamis et al., 2008).

3 Design of the NLT-enhanced Mobile Sales Assistant

3.1 Identification and evaluation of relevant sales questions

The first design-cycle of the current work has the objective to identify schemata of sales questions that are relevant in shopping situations in the domain of customer goods. These questions will directly guide the design of the NLT-MSA as described in Section 3.2.

For the identification of relevant sales questions, sales conversations and consulting talks concerning consumer electronics were recorded at a trade fair. Afterwards, the resulting speech corpus was transcribed. We derived a catalogue of sales questions and answers that was further analyzed regarding the communicative intentions of customers when posing a question. According to McKeown (1985) communicative customer intentions were identified based on the derived question structures in purchase conversations. Next, the range of sales questions triggered by each communicative customer intention was analyzed regarding their linguistic structures. Therefore, we derived 17 schemata of questions frequently occurring in the transcribed purchase conversations (cf. Table 1). Each question schemata is linked with a specific communicative customer intention and consists of a linguistic goal and the schematic structure of the question, etc. (Janzen and Maass, 2009).

#	Name of the question schema	Evaluated generic question	Mean	SD	p-value
1	Description_Information_Price	How much is this product?	4.78	0.42	< .001
2	Description_Decision_Comparison	Is there a cheaper product available?	4.52	0.64	< .001
3	Description_Information_PProperty	What are the properties of this product?	4.48	0.67	< .001
4	Description_Decision_Existence_Property	Does this product have a specific property?	4.44	0.60	< .001
5	Description_AlternativeProduct	Which alternative products are available?	4.37	0.65	< .001
6	Description_AdditiveProduct_Discount	Is there a bundle price for products A & B?	4.26	0.76	< .001
7	Description_Survey_NumberOfProperties	What are the options for a property of a product category?	4.04	0.82	< .001
8	Description_Survey_Average	How much is the average price of this product category?	3.94	1.12	< .001
9	Description_Decision_Existence_Product	Is this product available with option X?	3.93	0.82	< .001
10	Definition_Pure_Definition	What is the meaning of a product property?	3.80	0.76	< .001
11	Description_AdditiveProduct_Bundle_Price	How much is this product bundle?	3.78	0.98	< .001
12	Description_Information_PProperty	What is the value of a specific property of this product?	3.69	0.95	< .001
13	Description_AdditiveProduct_Survey_Matching	Which products fit to this product?	3.43	0.88	< .01
14	Description_Information_Usage	How to use this product?	3.35	1.18	< .05
15	Description_AdditiveProduct_Decision_Matching	Is Product A compatible with Product B?	3.30	1.11	< .05
16	Description_Information_Person	Who is the producer of this product?	3.02	1.16	>.05
17	Description_Information_Modality	How [big | heavy] is this product?	2.89	1.10	>.05
18	Description_Survey_NumberOfProducts	How many products have the property X?	2.80	1.11	>.05

Table 1. Ranked schemata of sales questions evaluated by 54 subjects. Note: SD = standard deviation; p-values result from one-sample t-tests (test-value = 3)

Having identified 17 schemata of sales questions, we have then evaluated generic questions of these schemata. The objective of this evaluation was to drop schemata that are not relevant in a shopping situation from a customer perspective. Each subject was shown the rather generic question together with a concrete example for better understandability. Then subjects had to rate each of these questions against the following statement on a five-point Likert scale that ranged from strongly disagree (1) to strongly agree (5): *This question is relevant to me in a shopping situation*. The rationale for this statement is derived from the compatibility construct of Innovation Diffusion Theory (Rogers, 2003). Compatibility is defined as the degree "to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters" (ibid., p. 240). In our work, innovation represents the question that a customer adopts in order to satisfy his or her information need in in-store shopping situations.

The result of this evaluation is presented in Table 1, in which the question schemata are ranked with regard to the mean values of the ratings. Overall, 19 female and 37 male students from a business school participated in the study. Their age ranged from 20 to 24 (n=34), 25 to 29 (n=13). Seven subjects were above 30. We have employed one-sample t-tests to see whether the mean values differ significantly from the Likert-scale's neutral test value three. That is, neither a positive nor a negative rating. This analysis shows that question schemata one to 15 lie significantly ($p < .05$) above the neutral test value and thus, are rated positive. However, the remaining schemata are not rated significantly negative. Thus, these schemata will also be taken into account for the development of the NLT-MSA in the second design cycle that is described in the following section.

3.2 Development and evaluation of the NLT-MSA

3.2.1 The NLT-enhanced interface

We started from the outset that a NLT-MSA needs to fulfill a set of requirements. First, the NLT-MSA has to process applied dialogs consisting of questions and answers in shopping situations. In order to realize such a communication, the NLT-MSA needs to resolve several, in part conflicting communicative intentions. Second, the NLT-MSA adopts a supportive function concerning the informational needs of the customer regarding the purchase decision that aligns with behavior of professional sales persons. Third, it has to represent information that it aligned with a retailer's economic interests. As the dialog interface represents a mobile shopping assistant in physical environments, an efficient NLT approach has to be assured. Hence, a fourth requirement is to provide input options as preferred by customers (cf. Table 1). Thereby the usability of the NLT-MSA can be improved (Warren and Pereira, 1982): "We believe that, for many purposes, a suitable natural language subset will be much preferred, on grounds of conciseness and ease of typing alone [...]". By a controlled language, we can constrain natural language so that it can be represented by a formal, but user-friendly query language.

Based on the findings of the first design-cycle, an NLT-MSA instance has been developed, which is called CoRA in the following. CoRA is implemented to support customers in purchase decisions within the cosmetics domain. It provides a question-and-answer interface between customers and physical products at the point of sale. All of the questions from Table 1 are available in CoRA. With CoRA, each customer is able to construct these questions term-by-term. But CoRA only suggests those question terms that result in meaningful questions. To improve the usability and acceptance, subjects are only asked to choose terms they are interested in by tapping with their finger: For example, *Which – products – fit*, as shown by the screenshot in Figure 1. Having tapped the last term of a question, the answer is presented together with the complete question on a second screen as shown in Figure 2. Analog to the analysis of questions, we analyzed collected answers of the aforementioned speech corpus of sales talks regarding their linguistic and intentional structure. We detected 12 answer types (cf. col. 3 in Table 2) and assigned them as well as the related retailer intentions to the customer intentions specified in the first design cycle. Table 2 shows the retailer intentions for participating in sales conversations contrasted with the communicative customer intentions. We assume that the satisfaction of information needs of customers when posing a question is the dominant intention from a retailer perspective. According to the 12 answer types represented as text plans that are able to generate answers related to the 17 question schemata, we derived 12 basic sales intentions (cf. col. 4 of Table 2). In addition to these basic retailer intentions, there are specific intentions that interfere with customer intentions, e.g., increase of profitability and revenue through bundle purchases (*Bundling*) or selling a product by a reservation price (*High_Price*). In our approach, retailer intentions are subordinated to communicative customer intentions (Beveridge and Milward, 2003) but conflicting intentions are resolved by a Natural Language Generation approach consisting of text plans in combination with various NLP approaches (Mann, 1984). Text plans are assigned to the question schemata (cf. col. 2 of Table 2) and define how effects can be achieved which satisfy customer intentions. It consists of a compulsive part that provides information requested by a customer, and optional parts, that conduce to the satisfaction of retailer intentions. The application of planning technologies allows an improved mapping of intentional structures (Moore and Paris, 1994) and provides a basis for realization of a resolution of conflicting goals of customers and retailers. Based on prior work (Stremersch and Tellis, 2002), bundling intentions of retailers have been integrated primarily into the answers given by CoRA.

Technically, CoRA is an OSGi plug-in of TNT2 that is a middleware for general Ubiquitous Information Systems (Janzen et al., 2010; Maass and Filler, 2006). The CoRA client is implemented on a mobile phone. It allows customers to identify a product by barcode via the phone's built-in camera (cf. Figure 3) and then to ask for product information (cf. Figure 4). The aforementioned question schemata are represented semantically in the CoRA knowledge base. Furthermore, product information is integrated into the NLT-interface based on a network of product ontologies. These ontologies are filled with product descriptions requested from repositories of manufacturers (Janzen and Maass, 2008).

#	Communicative Customer Intention	Answer Text Plan	Retailer Intention
1	Definition_Pure_Definition	IDENTIFICATION	Identification
2	Description_Information_Usage	FUNCTIONALITY	Functionality
3	Description_Survey_NumberOf Products	NUMBER_ PRODUCTS	Number_Products, Bundling
4	Description_Survey_NumberOf Properties	NUMBER_ PROPERTIES	Number_Properties
5	Description_Survey_Average	INFORMATION_ AVERAGE	Information_Average, Bundling
6	Description_Decision_Comparison Description_Decision_Existence_Product Description_Decision_Existence_Property	DECISION	Decision
7	Description_Information_Price Description_Information_Person Description_Information_Modality	INFORMATION	Information, Bundling, High_Price
8	Description_Information_Property	INFORMATION_N	Information_N, Bundling
9	Description_AdditiveProduct_Survey_Matching Description_AdditiveProduct_Decision_Matching	MATCHING	Bundling, High_Price
10	Description_AdditiveProduct_Discount	DISCOUNT	Discount, Bundling, High_Price
11	Description_AdditiveProduct_Bundle_Price	BUNDLE_PRICE	Bundle_Price, Bundling, High_Price

Table 2. Comparison of communicative customer intentions (question schema) and retailer intentions

3.2.2 Evaluation of the NLT-MSA instance

Having described the technical background of CoRA, we now present how this instance of a NLT-MSA was evaluated. The objective of this evaluation is to answer three questions: (1) Are NLT-MSA adopted by customers? (2) For which product domains are NLT-MSA predominantly relevant? (3) Are the questions provided by our NLT-MSA sufficient?

We evaluated CoRA against the following theoretical adoption constructs from IS research: perceived ease of use and perceived enjoyment, intention to use and finally, relative advantage compared to (1) static product information such as product leaflets and compared to (2) a sales talk. An experiment was conducted, in which each subject was asked to use CoRA to request information of several cosmetic products. The subjects had to ask the following questions to get used to CoRA and to be able to evaluate it afterwards: What is the price of the product? Which products fit to this product? Are there alternative products available? Are there less expensive products of this product category available? What is the average price of this product category? During the session lasting 30 minutes, further guidance was provided when a subject asked for additional help with CoRA. Then, in the second part of the experiment, the subjects were asked to rate questionnaire items with regard to the adoption constructs described above (Question 1). Consistent with prior research (e.g., Kamis et al., 2008), we adopted 7-point Likert scales that range from strongly disagree (1) to strongly agree (7). They were further asked to list relevant product domains for which they would use CoRA (Question 2) and to list additional questions to those given in Table 1 (Question 3).

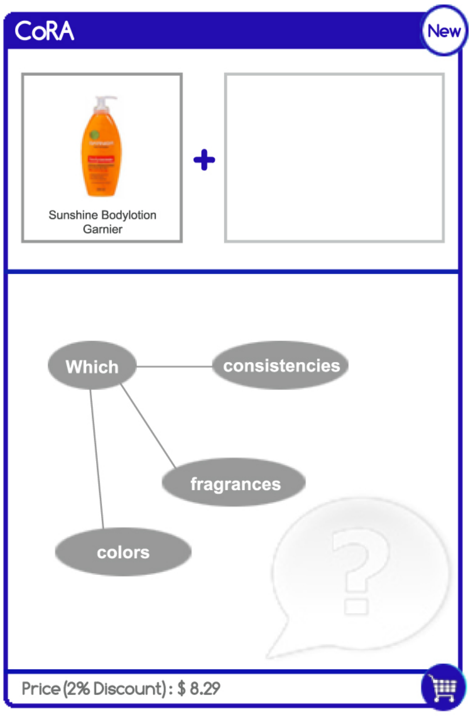

Figure 1. Step-by-step composition of a question

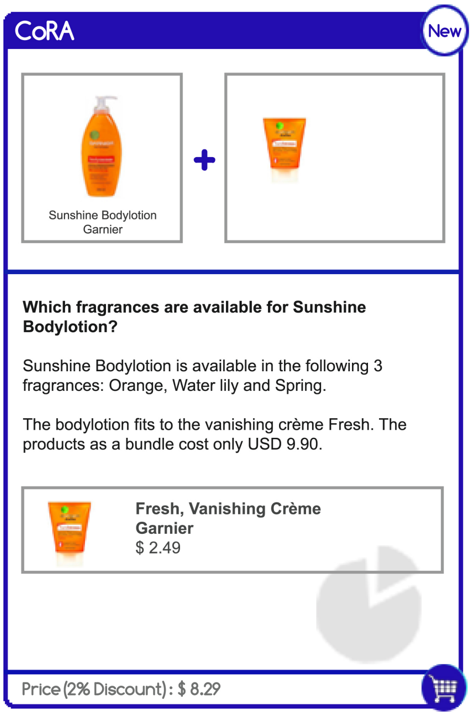

Figure 2. Presentation of the answer

Figure 3. Identification of a product

Figure 4. Interaction with CoRA

3.2.3 Results of the Lab experiment

The same sample population of the first design cycle was used. Regarding the first research question, we employed one-sample t-tests with a neutral test value of 4 to indicate whether CoRA was perceived significantly positive or negative by high or low utility scores. The descriptive statistics and results of the one-sample t-tests are shown in Table 3. All multi-item research constructs were reliable as Cronbach's Alpha lies above the recommended value of .70 (Nunnally, 1967). Results show that almost all constructs were perceived positive at the highest level of significance at .001. This supports the utility of CoRA for product information acquisition in in-store shopping situations. Only when compared to a sales talk, CoRA showed no significant relative advantage but also no significant disadvantage. We therefore assume that CoRA is comparable to a sales talk, which does not only strengthen its utility for customers but also for retailers that may offer such an application in addition to sales personnel. We thus can preliminarily answer the first research question by stating that our subjects would adopt CoRA for in-store shopping situations even though CoRA was configured to integrate bundling intentions of retailers in the given answers.

Construct	Items	Alpha	Mean	SD	p-value
Perceived ease of use of the NLT-MSA	3	.76	5.70	0.87	< .001
Perceived enjoyment of the NLT-MSA	3	.84	5.31	1.09	< .001
Perceived relative advantage of our NLT-MSA when compared to					
a) static product information	3	.75	4.59	1.26	< .01
b) sales talk	3	.80	4.03	1.25	> .05
Intention to use	1	n/a	5.59	1.39	< .001
Intention to prefer a NLT-MSA-enabled retail store	1	n/a	4.94	1.38	< .001
Intention to pay for the NLT-MSA application	1	n/a	4.20	1.38	> .05
Intention to buy a product after NLT-MSA use	1	n/a	5.07	1.41	> .001

Table 3. Descriptive statistics and results of the one-sample t-test for the 54 subjects; Note: SD = standard deviation; p-values result from one-sample t-tests (test value = 4)

Responses with regard to the second research question, i.e. relevant product domains, were consolidated and assigned to 13 separate product categories as shown in Figure 5. Two researchers conducted this categorization in order to assure reliability. The number of responses was then used to cluster the product domains. As a result, electronic consumer products together with groceries were the top-rated product domains followed by cosmetic products and fashion products. Only a few subjects of our study mentioned the remaining product domains. Even though twelve subjects found cosmetic products relevant, this result probably has a bias regarding the experimental scenario itself. We therefore dropped this product domain and conclude for the second research question that NLT-MSA are primarily relevant for customers that are going to buy consumer electronics, groceries but also, with less support, fashion products.

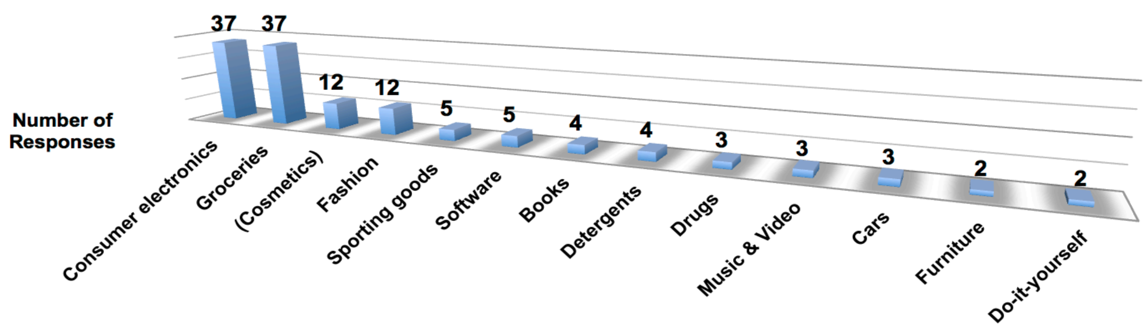

Figure 5. Frequency distribution of product domains relevant for NLT-MSA use based on 54 responses; Note: Cosmetics is bracketed due to bias considerations

Finally, answers with regard to the third research question were analyzed, i.e. if there were further customer intentions and corresponding question schemata in addition to those provided in Table 1. That is, we derived additional questions that were relevant to our subjects. Consistent with the procedure described in Section 3.1, we specified ten new question schemata. The results are shown in Table 4 with exemplary questions.

#	Name of the question schema	Exemplarily question
1	Description_Availability	Is the dress in stock?
2	Description_UserPreferences	Which cereal bar fit to my preferences?
3	History_Internal	Which products were considered by me?
4	History_External	Which products were considered by other customers?
5	InnerLife_Emotional	Is the cereal bar healthy?
6	InnerLife_Objective	Where was the cereal bar produced? How was the cereal bar produced?
7	Equation_Difference	Where is the difference between iPhone and Palm Pre?
8	Equation_Equity	Are the displays equal?
9	Validation_ExternalReviews	Are there expert reviews concerning the shampoo?
10	Validation_ExternalOffer	Where is the dress offered for less money? Where are alternatives offered?

Table 4. Additional question schemata

To consolidate both existing and new question schemata from both design cycles we developed a taxonomy and aligned it to the Simplified Customer Choice Model (SCCM, Maass and Kowatsch, 2008). The SCCM describes a purchase process consisting of four steps: (1) determination of the prototypical model of a product, (2) screening of available products, (3) scope extension (e.g., search for product bundles) and (4) choice making. With SCCM we were able to see which communicative intentions are relevant to each of these four steps. This procedural perspective may therefore inform the design of future NLT-MSA instances such that a customer is supported accordingly in each of these steps. Our taxonomy is shown in Figure 6 and represents the overall result with regard to the third research question. The rationale for this taxonomy is given in the following.

The first top-level customer intention is *Definition* (McKeown, 1985). It describes the definition of a product or a product feature. Based on the analysis of the question catalogue, the top-level intention is further divided into the intentions *Pure Definition* and *Functionality* that concern the pure definition of a product or feature as well as its functionality. Communicative customer intentions of type Definition are assigned to the first two steps of SCCM, i.e. determination of a prototypical model and screening. The second top-level intention assigned to the screening step of SCCM is *History.* It reflects customers' information needs towards a product during an ongoing sales dialog with CoRA (*Internal*) or by other customers (*External*). The third top-level customer intention is *Description* (McKeown, 1985). It characterizes questions that focus on information about single products, product bundles or specific product features. This intention covers the sub-intentions *Survey, Decision, Availability* and *Pure Information* that are assigned to the screening step of SCCM. These sub-intentions describe surveys of products concerning specific features (Survey), questions regarding the existence of products with specific features (Decision), the availability of products or product variants in stock (Availability) and questions about product features in general (Pure Information). In addition, Description also covers the following customer intentions assigned to SCCM's scope extension step: *Additive Product*, *Alternative Product* and *User Preferences*. Additive Product intentions describe matching products, prices of product bundles or bundle discounts, whereas Alternative Product represents information needs concerning alternative products with similar features. Lastly, User Preferences represents the linkage of user preferences with matching products. The forth top-level intention *InnerLife* is also assigned to the screening step of SCCM. It covers product information that is rather profound than obvious product features like price or color of a product. On the hand, one speaks about "emotional" information, e.g., if a product is "good" or "healthy" (*Emotional*). On the other hand, there is profound information that is more objective, e.g., how the product was produced (*Objective*). The fifth top-level customer intention is *Equation.* It represents comparisons of products regarding their *Difference* or *Equity*. As product comparisons extend the scope of a single product in terms of a product bundle, this top-level intention belongs to scope extension of SCCM. The last top-level intention is *Validation*. It represents a need for validation of an intended purchase in the choice-making step of SCCM. This validation can take place by asking for *External Offers* of products, e.g., by online shops, or *External Reviews* by other customers or experts.

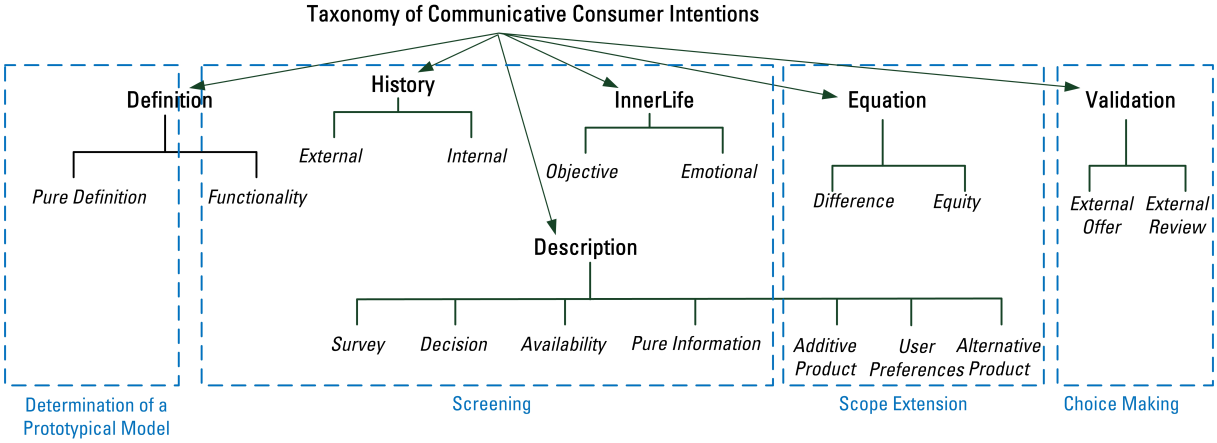

Figure 6. Taxonomy of communicative customer intentions applied to SCCM (dashed)

4 Discussion

Dialog-based interfaces that leverage NLT provide an innovative class of user interfaces that can be connected with various IS in different domains. With NLT-MSA we have shown how dialog-based interfaces can be used in sales situations for non-commodity products. Little evidences exist so far how dialog-based interfaces are adopted in real-world situations. Therefore we conducted a preliminary laboratory study with a prototypical NLT-MSA. This work was embedded into a design science methodology with a particular focus on elicitation of question-answer schemata that are perceived as being relevant in sales situations. On communication level, we considered conflicting interests between customer intentions and intentions of sales persons and tested that by the empirical study as well.

During our work over the last five years, we learned that few NLT tools are available that can be used for dialog-based interfaces in a straightforward manner. Therefore, we had to build the complete dialog-based interface from scratch. This might be the reason for sparse research on the use of NLT in IS in general (Storey et al., 2008; Suh and Jenkins, 1992; Vassiliou et al., 1983) and on dialog-based interfaces in particular. Hence, this paper presents insights in a class of interfaces that provides on one hand side interesting characteristics for innovative IS and is on the other hand quite complex for most IS research activities. Nonetheless, our results show that dialog-based systems are adopted in laboratory settings so that future field studies with retailers for various product classes look promising.

Sales situations are highly constrained by cultural knowledge and behavioral schemata. Hence, derivation and evaluation of question schemata give insights into deep cognitive and social structures that guide communication and social interactions in general. Test persons perceived the use of schematic dialogs as natural. Nonetheless it must be noted that these schemata are highly domain and situation dependent. The validity of our empirical results is therefore limited to the experimental setting, i.e. selection of cosmetic products and technical-savvy subjects. As a consequence, cross-domain studies in real-world environments will provide more insights in the use and fine structure of dialog schemata. Generally, structured natural languages provide efficient means for communication. Because customers refuse to talk to an NLT-MSA in a store, we used tree-based composition of sentences that support efficient generation of phrases by browsing through a network of words and phrases (Nikolova and Ma, 2008). Furthermore user communication with a system takes place in a goal-driven and concise way as well as without amenities. This means that the application of schemata constitutes an appropriate approach for natural language human-computer-interaction. As part of dialog schemas, we used congruent and conflicting intentions that govern dialogs in sales situations. Exemplified by *Bundling* intentions, we demonstrated how anticipated customer intentions can be extended by potentially conflicting sales intentions. On one hand, we have configured the NLT-MSA to use bundling intentions. On the other hand, we evaluated whether users adopted additional information that is not directly related to their anticipated intentions. As it was shown by our study, test persons perceived this dialog quite positive. The reason for this might be that this is a common sales strategy in retail stores.

But it is clear that this is only an early study on different types of intentions in sales and other business situations. Thus, important questions that guide our current and future research are: (1) How are congruent and conflicting intentions used by humans in business communication? (2) How can this be transferred to dialog-based interfaces?, and (3) Do dialog interfaces that support complex intentions provide tangible utilities, such as reduced cognitive load, improved decision quality and decision satisfaction, but also improved customer relationships, higher revenue, and higher profits?

5 Summary

In this work, we have presented a Natural Language Technology-enhanced Mobile Sales Assistant (NLT-MSA) for in-store shopping situations. Our NLT-MSA is innovative in the sense that it handles both intentions from a customer's perspective and from a retailer's perspective. We employed two build-and-evaluate loops guided by design science research. First, relevant customer intentions and corresponding question schemata have been identified. Second, the question schemata have been implemented in our NLT-MSA instance, whereas a bundling strategy was integrated as retailer intention. Subjects of a lab experiment (n=54) have evaluated our NLT-MSA quite positively for use in shopping situations related to consumer electronics and groceries. Finally, additional consumer intentions have been identified and consolidated into a typology that will guide our future work.

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