ELICITATING, MODELING, AND PROCESSING UNCERTAIN HUMAN PREFERENCES FOR SOFTWARE AGENTS IN ELECTRONIC NEGOTIATIONS: AN EMPIRICAL STUDY

Completed Research Paper

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Abstract

Transaction costs in electronic business may become marginal, since negotiation processes can be assigned to software agents which act autonomously on behalf of their human principals. This advantage makes electronic negotiations highly appealing to actors in various e-business areas, including online auctions and product configuration negotiations. However, software agents can negotiate appropriately only if the preferences of their principals are explicitly available. While this task has been acknowledged as crucial challenge, it has only rarely been investigated how preferences of human principals can be extracted and modeled. This paper addresses this research gap by suggesting, implementing, and empirically testing a preference elicitation method that is based on fuzzy set theory and accounts for the impreciseness and subjectivity of preferences. Our findings indicate that the proposed method is suited for elicitating fuzzy set based preferences. Furthermore, the fuzzy preference model can project human decisions more accurately than a traditional, crisp approach.

Keywords: Preference elicitation, Automated negotiation, Uncertainty, Fuzzy set theory, e-business

Introduction

People bargain and haggle about goods and prices on bazaars for centuries. Sellers on such marketplaces have a lot of ways to convince the buyer: They can reduce the price, add a freebie to the offer, or propose an exchange of goods. This negotiation can be a win-win-situation; e.g., a greengrocer can give away some of the vegetables she has in abundance and, by doing so, she can convince a buyer to buy some expensive fruits with high margins. Nowadays, bazaars and haggling are a bit antiquated. Commerce is characterized by given offers and catalogues and as customization and negotiation is a very expensive process, the cost is higher than its benefit in most cases. However, digitization and automation is ubiquitous. This development changes the way people do business again. In electronic business, the cost of negotiations has become marginal since the negotiation can be assigned to software agents, who decide based on the preferences of their human principals (Conitzer 2010b), but without any human intervention (Rudowsky 2004). The most prominent examples are bidding agents on online auction platforms (Sandholm 2002; Weinhardt 2005), automated supply chain negotiations (Arunachalam et al. 2005), or price and product configuration negotiations in electronic commerce (Yang et al. 2009). Furthermore, the consideration of negotiations is a key element for achieving external business integration (Markus 2000).

Apparently, the preferences of human principals play a key role not only in personal negotiations but also in electronic negotiations. Preferences can be conceived of as an individual's attitude towards a set of objects (Lichtenstein and Slovic 2006). In economics, preferences are often represented with real-valued functions, which assign real numbers to the set of objects. These numbers are usually referred to as "utility" (Arrow 1958; Fishburn 1970). However, people usually have difficulties in assigning precise utility values to objects, resulting in the need for conceptualizing uncertain preferences in terms of "imprecise and vague utility values". Additional to this impreciseness, human preferences underlie subjectivity (Bui and Sivasankaran 1991). Thus, a key concern in addressing uncertain human preferences in the context of electronic negotiations is the usage of a theoretical basis and models that account for impreciseness and subjectivity. The literature suggests many uncertainty theories, including various probability theories, fuzzy set theory (Zadeh 1965), expected utility theory (Bernoulli 1738), and prospect theory (Kahnemann and Tversky 1979), the appropriateness of which to be applied in a particular setting depends on their ability to consider the prevailing root of uncertainty (Zimmermann 2000). While uncertainty is explicitly covered in some IS subfields, including the evaluation of returns on IT projects (Banker et al. 2010), the literature on electronic negotiations is silent on how to use uncertainty theories in order to model the preferences of human principals. We argue that fuzzy set theory is appropriate, which leads to the formulation of our first research question: How can fuzzy set theory be used to model uncertain preferences in electronic negotiation settings?

Software agents in electronic negotiations need to act on behalf of individuals. Thus, preferences, which are implicit attitudes of individuals, need to be available in a processable format (e.g., to be used in electronic negotiation protocols) and must be made explicit with a representation form. This transformation of implicit preferences to explicit preferences is referred to as the process of preference elicitation, and it is regarded a major challenge in the consideration of human preferences (Lloyd 2003). Preference elicitation methods need to consider (a) the uncertainty model that is used to represent preferences and (b) the context in which preferences are elicited. While elicitation methods for uncertainty preferences have been proposed (e.g., Haddawy et al. 2003) and the fuzziness of preference is theoretically well covered (Zadeh 1965;1975a;1975b;1975c; Alonso 2009; Bui and Sivasankaran 1991; Dubois and Prade 1980), the literature does not provide methods that allow to model preferences with fuzzy sets (requirement a), to our best knowledge. In the context of electronic negotiations, such methods would also need to account for economic values in electronic negotiations (requirement b). Thus, our second research question is: How can uncertain preferences (represented with fuzzy sets) in electronic negotiation settings be elicited.

Both preference elicitation and representation are considered major problems in electronic markets (Beam et al. 1999). The issues become evident in online auctions: For instance, in eBay auctions, bidding the willingness to pay is the dominant strategy, as it represents a sealed second-price auction (Vickrey auction; Vickrey 1961). Nevertheless, many users raise their bid in the last seconds of the auction (Ockenfels and Roth 2002). This may result from users being unable to estimate precise values.

Our empirical study contributes to solving these problems by (1) suggesting a preference modeling approach drawing on fuzzy set theory as fuzzy set theory is able to account for subjectivity and express impreciseness (Zimmermann 2001), (2) proposing a fuzzy preference elicitation method, and (3) empirically validating our modeling and eliciting approaches in a web-based experiment that simulates a negotiation agent that bargains about the configuration of a laptop computer with several retailers.

The remainder of the paper is structured as follows: After this introduction, we present our theoretical framework that provides the theoretical basis for our work. Subsequently, we introduce the fuzzy preference model, the elicitation method, and our hypotheses. Afterwards, we describe our methodology and the design of the experiments. Thereafter, we present the results and implications of the empirical study and, finally, we give an outlook to future work and conclude the paper.

Theoretical Framework

Matching supply and demand in marketplaces is essentially based on arrangements between buyers (customers) and suppliers (vendors, sellers) regarding respective products (physical goods or services) and their characteristics (attributes). Often a potential buyer is not bound to getting some specific homogeneous commodity product, but a product may generally be substitutable by a different – yet similar – product. In other words, a potential buyer seeks a product which fulfills certain criteria regarding relevant characteristics. For example, someone who is looking for a new laptop computer may, on the one hand, have some mandatory features in mind (such as a specific processor and operating system), but, on the other hand, there are characteristics such as display size and the battery capacity where a buyer takes a set of feasible characteristics into account. The buyer's valuation of a product generally depends on the characteristics (and analogously for the supplier).

In this paper we are concerned with preference modeling and elicitation as well as achieving agreements in e-commerce settings. We aim for preference-based negotiation mechanisms for reaching agreements between buyers and suppliers considering customizable products with interdependent characteristics. In particular, we examine the impact of using different preference models in connection with agent-based negotiation procedures. In the following, we will first introduce the use of agent-based concepts for supporting market transactions. Then, we will be looking upon buyer's preferences, eventually focusing on the vagueness (fuzziness) of preferences and means for unveiling and using such preferences. Finally, we will discuss agent-based negotiation protocols that support the agreement phase in e-commerce transactions using elicited preferences.

Agent-Mediated E-Commerce

Since we live in a digital world with quasi ubiquitous availability of computing machines (such as stationary computers and mobile gadgets) and connectivity among them by the Internet (wired as well as wireless/mobile), e-commerce increasingly shapes market segments. That is, some or all parts of a market transaction (considering the information, agreement, and execution phase) may be partly or fully fulfilled automatically. However, to date, involved steps often critically depend on the intervention of involved human beings. For example, some potential buyer may use the web to look for fixed-price offers at online retailers or may successively enter bids using an online auction service. In order to increase the level of automation of market processes (as far as this may increase overall efficiency) digital business agents (software components/software agents) may take over steps that are as yet based on human intervention (Lomuscio et al. 2003). Resulting agent-mediated e-commerce concepts have to cope with several intertwined problems, in particular: How to represent the range of products and respective properties in an informational model? How to elicit buyer's preferences and represent them in a quantitative model? How to control the communication between potential buyers and suppliers in formalized interaction protocols (for different transaction phases)? Considering only the agreement phase in market transactions, such an interaction protocol is called negotiation protocol.

The first question is partly addressed by research on product taxonomies and related ontologies (Hepp 2006; Lee et al. 2006). In this paper we generally assume that the market transaction involves products with variable characteristics (instead of the simple case where a retailer offers products with fixed properties). For example, consider customizable products such as cars which are increasingly manufactured according to the wishes of the customers within the bounds of feasible car configurations.

E-commerce settings with customizable products can benefit both vendors and customers. The customer obtains a product which is a more valuable for this customer, and the vendor can increase sales and may still achieve efficient manufacturing processes (Chen and Kersten 2004). However, such win-win opportunities are put at risk if no reasonable coordination mechanism is available to achieve suitable agreements (Beam and Segev 1997).

Buyer's Preferences and Product Attributes

Buying decisions generally depend on buyers' preferences with regard to the available product set A. There is the common assumption that a rational person has a weak preference relation over A, which may be represented by on ordinal value function v (French 1986). If one also assumes that a potential buyer has weak preferences regarding the exchange of products (i.e., there is some notion of the strength of preferences and value differences), it is possible to represent buyer's preferences by a cardinal value function (French 1986). This allows measuring the value of a product in terms of a monetary value. Then it is reasonable to say that a potential buyer evaluates a given product by x monetary units (or that the value of exchanging two given products is y monetary units for some person). The perceived product value is in accordance with the willingness-to-pay (reservation price), i.e., the price at which a potential buyer is indifferent between buying and not buying (Moorthy et al. 1997).

As discussed, we assume that products are defined by a vector of characteristics (attributes, criteria, items) $a = a_1, \ldots, a_n$, with $a_i \in A_i$, $i = 1, \ldots, n$. Consequently, the actual set of alternative products A is defined as a feasible subset of the cross product $A_1 \times A_2 \times \ldots \times A_n$. Depending on the context the price can be considered as one of the attributes or not; in the following we assume the latter case, i.e., the price is kept separately.

Considering the connection of a potential buyer's evaluation of a product and the product's attributes we need to distinguish whether preferential independence of attributes is valid or not. Only if one assumes that a potential buyer can ascribe values to individual attributes which are unaffected from other attributes, it makes sense to compose the value function v as a sum of individual values $v_1 + \ldots + v_n$. However, potential buyers' preferences may show preferential dependence of attributes such as:

- Complementarity: The value of some attribute may be larger depending on a suitable setting of another attribute. This may be modeled as a super-additive term in the value function.
- Substitutability: The value of some attribute may be negatively correlated with another attribute. This may be modeled as a sub-additive term in the value function.

Such situations of preferential interdependencies are rather common. For example, a potential buyer of a laptop computer may prefer a high-class graphics device only together with a high-class display (complementary attributes) or she may be interested in either an internal optical drive or an external optical drive but not both (substitutable attributes). For further details on the interdependency of attributes and the impact on the overall value of decision alternatives we refer to the literature on multi-attribute value theory (French 1986).

Uncertain/Fuzzy Preferences

In practice one often has to cope with the (subjective) uncertainty that is inherent in human preferences (Zimmermann 2000). This challenge includes the choice of both an appropriate uncertainty theory for modeling and processing uncertain preferences. The domain of uncertainty modeling has a long tradition; see, for example, the work of Knight (1921), who established a taxonomy of uncertainty, including the difference between objective and subjective uncertainty. Several theories have been suggested (Zimmermann 2001, p. 119f), including various probability theories, evidence theory (Shafer, 1976), possibility theory (Dubois and Prade 1988), grey set theory, intuitionistic set theory (Atanassov 1986), rough set theory (Pawlak 1985), interval arithmetic, convex modeling (Ben-Haim and Elishakok 1990), and fuzzy set theory (Zadeh 1965). The latter theory has turned out to be a useful approach in the absence of statistical information and in the presence of subjective uncertainty (Zadeh 1965; Zimmermann 2000; Zimmermann 2001), thus providing a profound theoretical foundation for modeling users' uncertain preferences. Through its extensions to fuzzy numbers and fuzzy arithmetic, introduced by Dubois and Prade (1978; 1980), it also allows for quantitatively processing uncertain preferences. To sum up, fuzzy set theory and fuzzy arithmetic provide a promising theoretical and mathematical background for processing uncertain user preferences. We now provide a brief introduction into those foundations of fuzzy set theory, fuzzy numbers, and fuzzy arithmetic that we use in our work. We then provide an artificial example that shows how fuzzy set theory is able to deal with uncertainty in users' preferences.

Fuzzy set theory generalizes traditional set theory in such a way that it provides for a degree of membership with which an element belongs to a fuzzy set. This concept is in contrast to (crisp) set theory, where set membership is dichotomous. A specific type of a fuzzy set is a fuzzy number (Dubois and Prade 1978; 1980), which is formally defined by $\{(x, \mu_{\widetilde{N}}(x)|x \in \mathbb{R}\}$, $\mu_{\widetilde{N}}: \mathbb{R} \rightarrow [0,1]$ where $\widetilde{N}$ is referred to as fuzzy number.[1] $\mu_{\widetilde{N}}$ is denoted as the membership function of $\widetilde{N}$, and it outputs the degree with which $x \in \mathbb{R}$ belongs to N. It should be noticed that in contrast to a crisp number, a fuzzy number is a function that assigns each crisp number a membership degree with which the crisp number belongs to the fuzzy number. For example, the fuzzy number $\widetilde{20}$ may represent a user's understanding of "real numbers close to twenty" or "approximately twenty", and it may be given by the membership function $\mu_{\widetilde{20}}(x) = (1 + (x-20)^2)^{-1}$. Note that the membership function differs from a probability density function in two regards: Firstly, $\int_{-\infty}^{\infty} \mu_{\widetilde{N}}(x)dx$ does not need to equal 1, and secondly it mirrors the subjective attitude of an individual rather than reflecting statistical evidence.

Of particular importance in applied fuzzy set theory are triangular fuzzy numbers, where a triangular fuzzy number $N = (a, b, c)$, $a < b < c$, $a, b, c \in \mathbb{R}$, is a fuzzy set over $\mathbb{R}$, with the membership function

$$\mu_N(x) = \begin{cases} \dfrac{x-a}{b-a}, if\ a \leq x < b \\ \dfrac{c-x}{c-b}, if\ b \leq x \leq c \\ 0, \quad otherwise \end{cases} \tag{1}$$

The advantages of using triangular fuzzy numbers are that (1) they can be mathematically processed efficiently, and (2) their parameters a, b, and c can be comparably easily determined in practice. Their disadvantage may lie in their simplicity when empirical uncertainty cannot be appropriately modeled with a triangular shape.

We use (triangular) fuzzy numbers to model uncertain user preferences. Fuzzy arithmetic operations are defined by Dubois and Prade (1978) based on the extension principle (Zadeh 1975a; 1975b; 1976). Many different fuzzy comparison operators have been suggested in the literature; an overview is provided by Dorohonceanu and Marin (2002), who also suggest two new comparison operators. We use their "B2 method" as (from our perspective) its application provides more intuitive results than the other operators, with which the "B2 method" is compared in their paper.

Preference Elicitation

During past decades, preference elicitation has been one of the main themes in behavioral decision research (Slovic 1995) and has been applied to many domains, including auctions (Blum et al. 2004), decision support systems, negotiations (Chen and Pu 2004), and other e-services (Jannach and Kreutler 2005). Preferences can be considered at the individual level and at the group level, the latter including recommender systems (Hu 2010; Hu and Pu 2011) and group decision support systems. As the focus of this paper is on the individual level, we only provide a review of preference elicitation at the individual level.

We identified two main streams of research on preference elicitation (Chen and Pu 2004; Keeney and Raiffa 1976), which result from a hedonic approach where, first, the composite good being valued is reduced to its constituent parts or features which are valued separately, and, second, the single values of the parts or features are aggregated to an overall value of the composite good. The first stream is related to psychometric scale methods, which include Likert scale techniques, binary choice techniques (Cameron

[1] The membership function μ of a fuzzy number is required to ($c \leq a \leq b \leq d, a, b, c, d \in \mathbb{R}$): (1) be a continuous mapping from $\mathbb{R}$ to [0,1], (2) constant on (-∞,c]: $\mu(x) = 0\ \forall x \in (-\infty, c]$, (3) strictly increasing on [c, a], (4) constant on [a,b]: $\mu(x) = 1\ \forall x \in [a, b]$, (5) strictly decreasing on $[b, d]$, and (6) constant on $[d, \infty)$: $\mu(x) = 0\ \forall x \in [d, \infty)$.

et al. 2002; Kahnemann and Tversky 1979), multiple choice techniques (Cameron et al. 2002), and best-worse scaling (Louviere and Woodworth 1990; Finn and Louviere 1992; Marley 2009; Jaeger et al. 2008), which is derived from the method of discrete choice (Mueller et al. 2009) and in which a person is asked to select both the best and the worst option in an available (sub)set of choice alternatives. The literature also accounts for the elicitation of preferences under probability-based uncertainty (e.g., Haddawy et al. 2003) and for modeling uncertain preferences with fuzzy sets (e.g., Alonso et al. 2009), but we did not find any paper that suggests a method for the elicitation of values that help to shape the fuzzy sets. Thus, we needed to develop a new method, which is described in the succeeding section. The second stream is related to aggregation methods, in particular to methods that help determine attributes' importance. One group of methods is based on the Analytic Hierarchy Process (AHP) (Satty 1977; Satty 1980; Satty 1994), another important group is based on conjoint analysis, which can also be combined with fuzzy-based models (Turksen and Willson 1994).

Automated Negotiations

Comprehensive e-commerce approaches have to address all phases of a market transaction: gathering information, coming to an agreement, and execution (in particular delivery and payment). Depending on the circumstances some or all phases are to some extent implemented digitally. That is, software agents may execute certain tasks automatically (on behalf of human principals). These agents must be equipped with preference information of their human principal (Meyer and Eymann 2003). In this paper we focus on agent-based negotiation concepts for the agreement phase of market transactions. Negotiations are comprised of a sequence of interdependent proposals and decisions between the participants with the aim to come to an agreement (i.e., conclusion of a contract) with respect to the negotiation object. In particular agents may negotiate about prices, e.g., as bidding agents in an auction (Bichler et al. 2003). Auctions constitute an important subset in the field of negotiations. Simple auction types are primarily targeted at determining prices and allocations of a single product to be sold (auctions) or bought (reverse auctions) in multilateral settings (Stroebel 2000). Combinatorial auctions are used to simultaneously allocate a set of products taking into account super- and/or sub-additive product bundle evaluations by the bidders (Cramton et al. 2006; Pekec and Rothkopf 2003; Strecker 2003). While so-called multi-attribute auctions have been proposed to cope with determining not only prices but also additional product attributes, these procedures deviate from classical auction procedures; for example, related procedures include specific iterative bidding/allocation steps and optimality cannot be guaranteed (Ronen and Lehmann 2005; Engel and Wellman 2010).

While many negotiation procedures have been proposed in the literature there is a great need for mechanisms which consider multi-attribute negotiation objects (Lai and Sycara 2009) instead of focusing on a single issue such as the price of a product (e.g., by some bargaining procedures with a limited number of offers and counter-offers on the price of a product). Negotiation approaches may be classified with respect to aspects such as:

- Negotiation object: price, quantity, product type, product attributes (or any combination of the listed elements, or any other complex structure that is representable as a formal contract set);
- Negotiation participants: 1 supplier and 1 buyer (1:1), 1 supplier and many buyers (1:*n*), many suppliers and 1 buyer (*n*:1), many suppliers and many buyers (*n*:*m*);
- Negotiation protocol: rules for the interaction (i.e., the communication) between buyer and supplier for eventually determining an agreement;
- Automation: fully, partly, or no automation of different steps of the negotiation protocol.

Obviously these aspects are interdependent. For example, the classical English auction protocol (Conitzer 2010a) determines price and allocation of a single homogenous product (offered by 1 supplier) to one out of many potential buyers. Negotiations often address 1:1 situations. That is, one is looking for suitable coordination mechanisms to exploit win-win opportunities between a buyer and a supplier.

Considering the participants of the negotiation, one usually has to cope with information asymmetry (Fink 2006). That is, no one else than some specific buyer knows about its preferences (private information) (Kraus 1996). Consequently, in such situations solution concepts that are discussed in cooperative game theory can usually not been applied, but rather one has to conform with certain restrictions according to assumptions of non-cooperative game theory (Klaue et al. 2001). In particular, the participants may behave strategically, i.e., they opportunistically pursue individual goals. While rules may be designed to restrict the participants' behavior, only rules which are verifiable can be effectively imposed (taking into account information asymmetry).

Research Model

A Fuzzy Preference Model

Having defined fuzzy numbers and fuzzy arithmetic in the previous section, we now explain how and motivate why subjective preferences of users are modeled using fuzzy numbers. We first provide a simple motivational example that shows how modeling users' preferences with fuzzy numbers can avoid failures of preference determination in the absence of the consideration of uncertainty. We then show how we use (simple) triangular fuzzy numbers to model the values (which represent users' preferences) that specific contract items have for users.

In our artificial example, we assume that we have an arbitrary number of agents and, for simplicity, three items per contract which represents the configuration of a product with three binary characteristics. An agent j's utility value of combining two characteristics p and q is generally represented by $P_j(p,q)$. For some agent j, let the utility values per item be $P_j(1,1) = 20$; $P_j(2,2) = 21$, and $P_j(3,3) = 20$ ($P_j(p,q) = 0$ in all other cases – for now ignoring interdependencies for demonstration purposes). An additive common preference model, as discussed earlier, is supposed. Furthermore, we assume that the elicitation of utilities of agent reveals that the utility values of items 1 and 2 are based on an optimistic assessment (i.e., the utility values of items 1 and 2 are probably "a bit" lower than 20 and 21, respectively), while the evaluation of item 3 is based on a more pessimistic approach. Reflecting these biases, the direct comparison of contracts $c_1 = (1,1,0)$ and $c_2 = (1,0,1)$ is likely to make agent j prefer contract c_2 over contract c_1. However, the application of (crisp) common preference delivery would result in the opposite, thus wrong order as $U_j(c_1) = 41 > 40 = U_j(c_2)$.

Figure 1 shows how using fuzzy numbers (representing subjective preferences) can deal with imprecise preferences and avoid deriving a faulty contract order. In each subfigure, the x-axis represents the economic value in currency while the y-axis represents the degree of membership. Please notice that fuzzy values are not crisp, but functions. While subfigures a), b), and c) show the utilities of single items, subfigure d) shows the preferences of the two contracts $c_1 = (1,1,0)$ and $c_2 = (1,0,1)$. Applying appropriate fuzzy operators results in the preference order $U_j(c_1) = \widetilde{41} < \widetilde{40} = U_j(c_2)$, which mirrors the actual preference order of agent j.

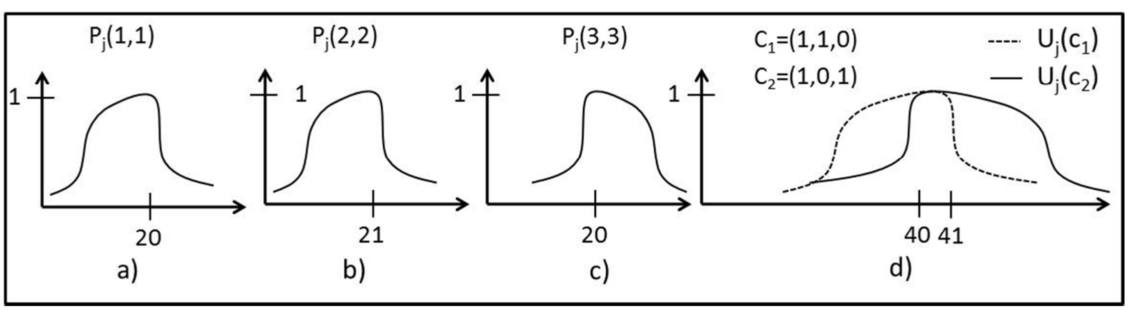

Figure 1. Fuzzy Utilities and Preferences of the Example

We already motivated the use of triangular fuzzy numbers to model users' preferences in the previous section. While in the context of certain preferences, users are required to specify the value of a specific contract item with a fixed number, in a fuzzy setting the user specifies the values of a specific contract item, e.g., the feature of a built-in DVD drive in a laptop, with a triple of values (a,b,c), where b represents the amount of money that – based on the subjective assessment of a user – represents best, i.e., with the highest degree of membership in fuzzy set theory language, the value of the item for the respective user, a represents the maximum amount of money (smaller than b) that does not represent at all, i.e., with membership value zero, the value of the item for the respective user. The value c is defined analogously to the value *a*. Figure 2 illustrates the meaning of the triple of values of a triangular fuzzy number in the context of modeling uncertain preferences.

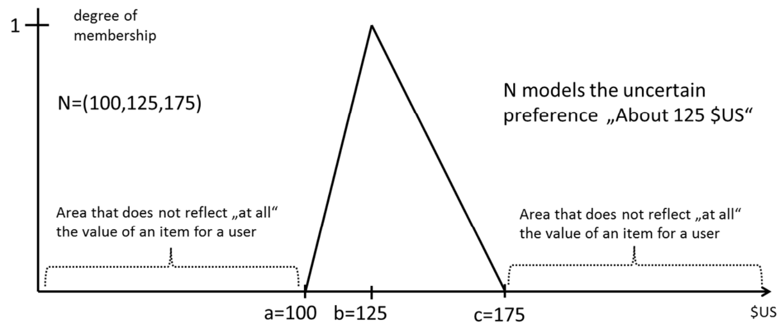

Figure 2. Triangular Fuzzy Number in the Context of Modeling Uncertain Preferences

Having defined the underlying mathematical and theoretical basis of modeling uncertain preferences, one key challenge remains: how can the values for *a,b,c* be empirically determined? We address this issue of preference elicitation in the succeeding subsection.

Fuzzy Preference Elicitation

As our review on preference elicitation methods above reveals, the literature does not provide a method for elicitating values that help determine the shape of triangular fuzzy numbers. Indirect approaches like the conjoint analysis are too excessive and time-consuming for preference elicitation for software agents. Thus, we propose (and implement) a new method, which aims at identifying values for all three parameters *a*, *b* and *c* of the triangular fuzzy number (see Figure 2 in the previous subsection). Our task is finally to define questions with which we extract from the user's mind the three values of a particular item.

In order to elicitate the three values *a, b*, and *c* we follow a market-based approach. We argue that an individual has a specific amount of money (b_2) in mind which s/he is willing to pay "without any doubt", and also an amount of money (*c*) above which s/he is definitely not willing to buy. While the value b_2 is difficult to elicitate from the user's mind, the value for *c* is easier to identify. We use the following question for this (in the sample case of a specific laptop configuration) (see Figure 3i)):

> **Value c**: *"Assuming you are eager to buying this laptop immediately, how much would you be willing to pay at most (buying price close to the bone)?"*

Analogously, we determine value *a* by asking the following question (see Figure 3ii)):

> **Value *a***: "Assuming you need to sell this laptop immediately, how much would you need to get at least (selling price close to the bone)?"

The logical composition of the fuzzy sets shown in the parts i) and ii) of Figure 3 results in a new fuzzy set "*I am willing to buy and I am willing to pay*", which is shown in part iii) of Figure 3 and which represents the uncertain value that is assigned to the laptop by the individual. However, while the new fuzzy set is already a (trapezoidal) fuzzy number, we do not have the values for b_1 and b_2 available. Thus, we approximate the trapezoidal fuzzy number by a triangular fuzzy number (part iv) of Figure 3). The advantage of this approximation lies in the opportunity to elicitate a value for *b* (with $a<b<c$) by asking the following question, which is straightforward to answer:

> **Value *b***: *"How much are you willing to pay (normal price) for the laptop?"*

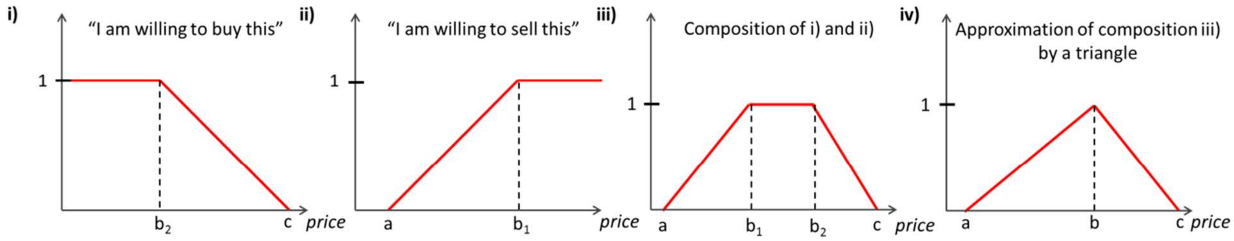

Figure 3. Concept of Fuzzy Preference Elicitation

In order to guarantee the consistency of values, i.e., to ensure that $a<b<c$ holds, we put a notification to each page of the survey: "*Please, notice the following constraint: Minimum < normal price < maximum*".

Hypotheses Development

In the following, we present four sets of hypotheses regarding different issues: (1) interdependencies, (2) degree of uncertainty, (3) preference prediction, and (4) preference simulation.

As argued in the theoretical framework, there are potential interdependencies of product attributes, which can be a major issue in negotiations as they may lead to nonlinear value functions (Klein et al. 2003). Since most coordination mechanisms are not able to overcome local optima, the nonlinearity of value functions exacerbates the negotiation (Fujita et al. 2010; Lang and Fink 2012).

***H1**: Value functions may be nonlinear resulting from interdependencies – such as complementarity or substitutability – between certain attributes.*

The fuzzy preference model is based on the hypotheses that human preference estimation is subjective and imprecise. This phenomenon is particularly important when users' maximal purchase and minimal selling price responses significantly differ from their worth estimation. We measure the degree of uncertainty (fuzziness) of a preference by the width of its fuzzy set, i.e., the larger the interval of the triangular fuzzy set the fuzzier the preference is. We hypothesize that with increasing level of domain knowledge the fuzziness declines since the user should be more likely to have a sense for valuations and can state their preference more accurately. Furthermore, users which recently informed themselves about prices due to a purchase or the intent to purchase are also less imprecise about their preferences as they know about current market prices as well as price ranges and have more intensively thought about the valuation of potential attributes.

***H2a**: Preferences are fuzzy, i.e., users are incapable to state accurate values.*
***H2b**: Domain knowledge decreases the degree of uncertainty.*
***H2c**: A recent purchase or the intention to purchase decreases the degree of uncertainty.*

In the third set of hypotheses, we consider the prediction power of the fuzzy preference model. Concerning this, we evaluate how well a fuzzy-set based preference model matches users' preferences compared to a crisp preference model. One of our central hypotheses is that the fuzzy model outperforms the crisp model. The fuzzy model extracts further information about the preferences, which cannot be utilized if there is no or little uncertainty, i.e., the less crisp the preferences are the better the fuzzy approach should project the preferences. Thus, fuzziness of preference should improve the model's performance. We expect that users with domain knowledge are able to express their subjective preferences more accurately, because they should be able realize more nuances. That is why we expect an improvement of the fuzzy model for knowledgeable users. Furthermore, the applied fuzzy comparison method, the "B2 method" by Dorohonceanu and Marin (2002), does not differentiate between fuzzy sets with the very same peak value if they are symmetric. Consequently, we hypothesize that increasing asymmetry leads to better results as it enlarges the differences to the crisp preference and reveals subjective biases.

***H3a**: The fuzzy preference model predicts preferences better than the crisp preference model.*
***H3b**: The fuzziness of preferences increases the prediction ability of the fuzzy model.*
***H3c**: High domain knowledge increases the prediction ability of the fuzzy model.*
***H3d:** Asymmetry of the fuzzy sets increases the prediction ability of the fuzzy model.*

Finally, regarding the performance of the fuzzy preference model in a negotiation setting, the reasoning is analogous to the set of prediction ability hypotheses (*H3*): fuzziness of preferences, domain knowledge, and asymmetry should have a positive impact on the performance of the fuzzy preference model in the negotiation.

***H4a**: The fuzzy preference model is superior in negotiations compared to the crisp preference model.*
***H4b**: The fuzziness of preferences increases the negotiation performance of the fuzzy model.*
***H4c**: High domain knowledge increases the negotiation performance of the fuzzy model.*
***H4d:** Asymmetry of the fuzzy sets increases the negotiation performance of the fuzzy preference model.*

Experiment Design

To test our hypotheses, we designed and built a web-based experiment tool. The tool aims at collecting preference data, testing preference mapping, and simulating negotiations. Furthermore, we have surveyed personal background data about the test persons.

Conduction

In the experiment's scenario, the users enter their preferences into a negotiation program, which negotiates customized laptop configurations with different retailers (likewise Yang et al. 2009).

The web-based experiment consists of four parts: (1) the fuzzy preferences elicitation, (2) pairwise comparisons between given configurations, (3) pairwise comparisons between fuzzy and crisp negotiations, and (4) background data elicitation. The experiment tool was implemented using PHP, JavaScript, and an SQL database system. Web-based experiments are highly efficient, because they can easily acquire great a great number of test persons and are flexible, i.e., they can interact with the user (Reips 2000). Moreover, since negotiation software is typically a web application, a web-based tool is highly suited for this application domain.

We followed an A–B single-subject approach for the experiments with crisp modeling as baseline and fuzzy modeling as alternative procedure (Robson 2011). Regarding the test person selection, we did not have any requirements for participants, as fuzziness of preferences is a ubiquitous issue. The participants were mostly researchers and scholars with a background in economic sciences. To increase the sample size, we partly draw on a crowdsourcing platform, a micro task marketplace. Clustering of test persons was made ex post facto by statistical analysis based on background data and preference properties.

To ensure a user-friendly test environment, we conducted a pretest with 18 participants to evaluate the experiment tool. All participants of the pretest were academics – partly experienced in empirical practices – and the tool was revised considering their suggestions and comments. Moreover, results from the pretest were used to parameterize the fuzzy comparison operator. To acquire a sufficient number of participants, we introduced a lottery as incentive raffling a $65 coupon of a well-known online retailer. Lotteries are considered as an efficient and cost-aware mechanism to attract and motivate study participants (Azzara 2010; Göritz 2004).

Preference Setting

Product Configuration

We have supposed that a laptop has eight customizable **characteristics** with two potential attribute values (see Table 1). Certainly, there are a lot more conceivable characteristics as well as domain values, but we limited them, as adding further possibilities would have extended the elicitation to an untenable length of time for the test persons. The eight characteristics with two potential attribute values each constitute 256 potential configurations.

Table 1. Overview Laptop Characteristics and Attribute Values				
Characteristic	(1) Display	(2) Hard disc	(3) Processor	(4) RAM memory
Attribute Values	12" 14"	500 GB 1000 GB	2x 3 GHz 8x 3 GHz	2 GB 8 GB
Characteristic	(5) Battery life	(6) DVD drive	(7) Manufacturer	(8) Support
Attribute Values	3 h 6 h	none built-in	NoName Samsung	none +2 years warranty

Regarding **interdependencies** between characteristics, we have supposed that *processor and RAM memory* as well as *manufacturer and support* are interdependent.

A fast processor needs sufficient RAM memory to use its full capacity and vice versa, otherwise, one of those two characteristics would represent a performance bottleneck. Therefore, we argue that the value of a fast processor combined with a large memory is higher than the sum of single aspects (complements).

On the contrary, a laptop by a well-known manufacturer such as Samsung might be more reliable than a laptop by an unknown manufacturer making an extra two years of warranty obsolete. Thus, we argue that the value of a well-known manufacturer combined with extra warranty is less than the sum of single aspects (substitutes).

Computation of Utility Values

During the experiments, we have to compute utility values based on the elicitated preferences (see next section). For the computation, we assumed an additive utility model summing up all valuations of attributes as well as its combinations (see Formula (2)).

$$U_j = \sum_{k=1}^{N} \sum_{l=k}^{N} P_j(k,l) * c_k * c_l \tag{2}$$

with j:user; N:number of attributes values; U_j:valuation of configuration; P_j:valuation of attributes; c_k:binary selection of an attribute

Whereas the crisp model simply sums up common valuation values, the fuzzy model sums up triangular fuzzy sets. This means that in the crisp model U_j and P_j are a single value, while in the fuzzy model U_j and P_j consist of a lower bound, an upper bound, and a peak value. Concluding, the crisp model draws on standard arithmetics and the fuzzy model on triangular fuzzy sets for the computation of utility values of product configurations.

Methodology of Elicitation

For the preference elicitation, we have used the proposed fuzzy preference elicitation method drawing on free estimation of the worth of a characteristic or a combination of characteristics as well as absolute purchase price and selling price limits. Since combinations of characteristics are difficult to imagine for test persons, we designed a mental support. At first, we asked the test persons for their evaluation of a basic configuration, which contains the respective inferior attribute value (we have assumed that the lower-positioned attribute values in Table 1 are at least as good as the upper-positioned). Furthermore, according to our proposed method, we asked the test persons for their purchase and selling price limit given they would intend to sell or buy the configuration. In the next step, we presented two different configurations: the basic configuration as well as a modified configuration. The modified configuration contained mutations in one or two characteristics and the test persons were asked to evaluate how much more they would be willing to pay. By doing so, we successively ascertained the test persons' estimation of single characteristics (24 questions) as well as the presumed interdependent combinations (6 questions). Invalid or incorrect answers were retained and given back to the test persons, as commonly handled in web-based surveys (Baron and Siepmann 2000). The ordering of the questionnaire was non-randomized. Related characteristics were asked subsequently to guide the test persons and keep up a logical flow, which is an important issue of questionnaire designing (Guy et al. 1987). The value of a configuration results from the sum of the value of the single attributes as well as interdependencies added to the value of the basic configuration.

Comparison of Fuzzy and Crisp Preferences Modeling

Experiment 1: Contracts without Prices

To examine the ascertained preference information, we presented two similar laptop configurations to the users and asked which one they would prefer or whether they are indifferent. This procedure was repeated ten times per user. In each of the ten pairs, one configuration was generated randomly and the corresponding second configuration had an equal number of improvements and deteriorations compared to the first one. For instance, we increased the RAM memory, but decreased the battery life. The hypothetical offers did not include prices, i.e., just characteristics were relevant. Thus, we constructed trade-offs between attributes and confronted the user with borderline cases. The configurations were the very same for each of the users. Subsequently, we simulated potential negotiation agent decisions for these borderline cases. In the fuzzy simulation, we drew on the triangular fuzzy set and the fuzzy comparison operator presented beforehand. In the crisp simulation, we used the mid-level value of the triangular fuzzy set only and drew on the regular arithmetic operator. We coded the choice of a configuration with 0 or 1, respectively, and assigned 0.5 for indifferent answers. Finally, we computed the gaps between the projections of the crisp as well as fuzzy modeling and the submitted user decision.

Experiment 2: Simulation of Negotiations

In the second experiment, we simulated product configuration negotiations with ten different laptop retailers using different preference models. The retailers were given different cost structures, i.e., their costs for different configurations differ, which leads to different negotiation outcomes in most cases. To obtain realistic cost structures, we ascertained retail prices for the attribute values and assumed that the retailers would bear costs in the amount of 50% and 90% of those prices (uniformly distributed). The laptop retailers determine their prices by adding a mark-up of 50% to the cost. This leads to higher prices for the single characteristic; however, since further characteristics – such as keyboard, loudspeaker, or case – are neglected and assumed as given, the resulting prices were realistically represented.

We chose a very elementary negotiation protocol (see Figure 4): Starting with the basic configuration, the retailer proposes two mutations of the configuration draft, i.e., she changes two attribute values, and the negotiation agent of the user decides if these mutations are accepted or rejected. If the agent rejects the proposal, the configuration draft remains and the retailer mutates it again; if the agent accepts the proposal, the mutated configuration becomes the configuration draft. This procedure is repeated until a predefined number of rounds is reached (initially, we chose 1,000 rounds).

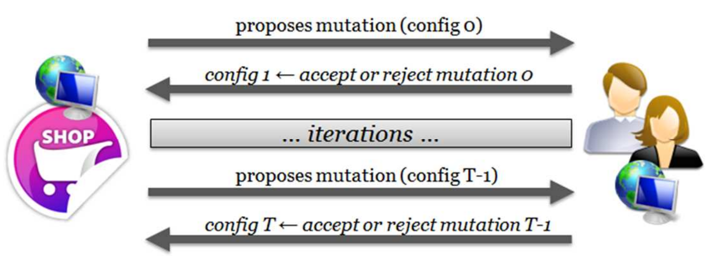

Figure 4. Negotiation Protocol

We assumed that the retailers are just interested in finding the best configuration for the customer, as they have an assured profit through the fixed mark-up. The customer's negotiation agent decides according to the user's input, the preference model, and the price.

We simulated the negotiation using the crisp as well as the fuzzy preference model. If both preference model approaches returned the same configuration, we started the negotiation over (but at most 10 times). Finally, for every retailer, we presented both, the fuzzy and the crisp negotiation outcome, to the user and asked which one they would prefer or whether they are indifferent. The order of displaying the outcome was randomized to prevent an order bias (Lee 1975).

During the conduction of the experiment, the results revealed that there is no statistical significance for the given setting and both preference models performed approximately equally. After these first results, we supposed that 1,000 rounds for 256 configuration possibilities do not reveal the quality differences of the preference models. So, we revised the experimental setup and extended the characteristics by adding three further features: a docking station, an office suite, and an integrated webcam. Including these new characteristics, the number of potential configurations increased to 2,048. To induce further scarcity, we set the number of negotiation rounds to 100. This ratio of configurations and negotiation rounds fits the real world better. Supposing there were twelve characteristics with five attribute values, the number of potential configurations would rise to over 244 million – a number too large to be tested enumeratively. Independently from the revisions of experiment 2, the setup of experiment 1 remained unchanged.

Background Data

To statistically test for influencing factors, we asked the participants to provide some background data before finishing the survey. Besides demographic data such as age and sex, we asked whether they had purchased a laptop in the last six months and whether they intend to buy a laptop in the next six months. Furthermore, we were interested in the technical skills of the test persons which represent domain knowledge. To determine these, we quizzed the participants about computer related topics like, e.g., acronyms ("RAM"), Wi-Fi encryption, or properties of a DVD. This quiz consisted of five yes or no questions including the option to admit lack of knowledge in each question. Finally, the participants could enter their e-mail address to join the lottery.

Results

493 persons started the survey, 210 of whom finished the questionnaire entirely (dropout rate: 57%). The responses were reviewed manually for inconsistent and unreasonable patterns such as highly repetitive values for different attributes, adding or subtracting just one unit to the middle value of the fuzzy set, or absolute instead of comparative ones. Finally, we got 151 valid data sets, 55 of which acquired by crowdsourcing on a micro task marketplace. The population of 151 respondents consisted of 114 male and 37 female test persons with an average age of 27.4. 117 of the test persons were younger than 30. The test persons answered averagely 3.1 of the five technological knowledge questions correctly, whereby 89 could answer less than four correctly. 31 respondents stated that they have bought a laptop in the last six months and just one respondent intends to buy one in the upcoming six months.

Preferences

At first, we take a closer look at the properties of the preferences such as interdependencies and degree of uncertainty. We then describe the results of the two experiments.

Interdependencies

In the previous section, we hypothesized that processor and RAM as well as manufacturer and warranty are interdependent. To verify this, we computed the relative differences between the sum of the values of the single attributes and the stated values of the combination of those attributes.

Regarding the combination of processor and RAM, we presumed that they are complements; however, on average, the combination was estimated with 2.1% less worth. The combination represented a complement for 38 respondents, and 86 assessed it as a substitute (27 had the very same valuation).

Regarding the combination of manufacturer and warranty, we presumed that they are partly substitutable. Here, the data supports our supposition. On average, the combination of both was estimated with 12.7% less than the two attributes on their own. 31 respondents assessed it as a complement and 102 as a substitute (18 had the very same valuation).

The figures show that there are different evaluations so that we can confirm hypothesis *H1*. Unlike our intuition, the ascertained data indicates that both combinations are substitutes for the most people, i.e., they are subadditive. Another explanation besides concrete interdependencies could be that there is a diminishing marginal value for combinations. In microeconomic theory, Gossen's First Law says that the more of a good an individual consumes, the less marginal benefit the individual gets for it. Analogously, there could be a diminishing valuation of more attributes in our case. Nevertheless, regardless of the interpretation, interdependencies can lead to nonlinear contract spaces and exacerbate the negotiation.

Degree of Uncertainty

We measured the degree of uncertainty through the willingness to pay (WTP) adjusted by the fuzzy set width, i.e., left and right values of the triangle divided by the middle value.

In hypothesis *H2a*, we assumed that preferences are fuzzy. Although our experiment design forces the test persons to state a fuzzy set (with minimum < middle value < maximum), the test persons are not urged to express a certain interval width. As shown in Figure 5, the estimated fuzzy set width significantly differs from values near to zero. Averagely, the fuzzy set width was 56% (30% mark-up and 26% mark-down to the approximate value; see Figure 5). The data gives strong evidence that the hypothesis *H2a* can be confirmed.

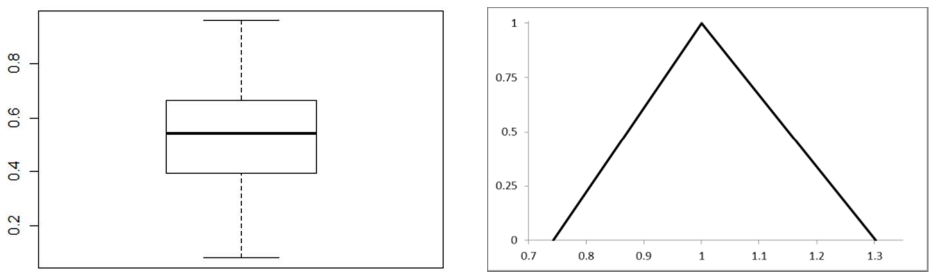

Figure 5. Boxplot of the Fuzzy Set Width (Without Outliers) and Average Fuzzy Set

To test our hypotheses *H2b* and *H2c*, namely the influence of technological knowledge and information, we conducted a linear regression on the fuzzy set width (see Table 2 / Formula (3)).

$$y_i = \beta_0 + \overrightarrow{\beta_i X_i} + \varepsilon_i \quad \text{with} \;\; \varepsilon_i \sim \mathcal{N}(\mu, \sigma) \tag{3}$$

The results show that there is no significant influence of technological knowledge on the degree of uncertainty so that we reject hypothesis *H2b*. However, *H2c* can be confirmed as information due to a purchase has a significant negative effect. If a test persons has bought a laptop in the last six months (just one person intended to buy one), the fuzzy set width was averagely 15.5% smaller. Further results are that test persons over 30 had a smaller uncertainty and the more time a test person spent for answering the survey, the less fuzzy her responses were (0.5% less fuzzy set width per additional minute).

Table 2. Linear Regression of Degree of Uncertainty

dep. variable	**description**			
degree of uncertainty	WTP adjusted fuzzy set width			
indep. variable	**description**	**Estimate**	**Stand. Err.**	
(intercept)	regression constant	**0.5521**	0.0428	***
technological knowl.	1, if 4 or 5 answers correct / 0, otherwise	-0.0261	0.0455	
informed	1, if purchased recently or intend to purchase / 0, otherwise	**-0.1546**	0.0534	**
Sex	1, if female/ 0, if male	0.0295	0.0538	
age	1, if 30 or older / 0, if younger than 30	**-0.1695**	0.0534	**
time	time spent for answering (in minutes)	**0.0048**	0.0019	*
data sets: 151 R^2: 0.1394	*signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*			

Experiment 1

In experiment 1, we ascertained the differences between the fuzzy and crisp choice projection and the user's choice for pairs of configurations (borderline cases). At this, we coded the decision with binary values (i.e., 0 and 1), if there was a clear choice, or with 0.5, if there was indifference between the two configurations. The difference between the projection value and the real value constituted the projection error.

The error of the fuzzy model was 40%, whereas the crisp model had an error of 42%, i.e., both models did not perform very well; however, the experiment concerned borderline cases. The fuzzy preference model projects the preferences better than the crisp model with a p-value of 2.23% (Wilcoxon signed rank test), i.e., we can confirm hypothesis *H3a*.

To evaluate the other hypotheses regarding preference projection, we conducted a probit regression (see Table 3 / Formula (4)).

$$y_i = \beta_0 + \overrightarrow{\beta_i}\overrightarrow{X_i} + \varepsilon_i \quad \text{with } \varepsilon_i \sim \mathcal{N}(0{,}1);\ y_i \epsilon \{0;1\} \tag{4}$$

In contrast to our hypotheses, technological knowledge, information, and interdependencies do not have a significant influence on the fact whether a test persons benefits from the fuzzy model or not – so we reject hypotheses H3b and H3c. However, the findings are that asymmetry improves the performance of the fuzzy model so that we can accept hypothesis H*3d*. As argued before, asymmetry can have an impact on the fuzzy comparison operator and increase the differences to the crisp model. If a fuzzy preference set is asymmetric, the test person expresses a subjective tendency towards more or less than her approximate estimation. This is a strength of the fuzzy model, which is not feasible in the crisp case. As asymmetry and degree of uncertainty are correlated (Pearson' r), we introduced an interaction term between those two variables. This interaction term is significant as well. If asymmetric fuzzy sets come along with a high degree of uncertainty, there are is an opposed, negative effect. We presume that if there were a high uncertainty and asymmetry, the respondents had a high indetermination regarding their valuations.

Table 3. (Linear) Probit Regression for Experiment 1

dep. variable	**description**			
fuzzy projection	1, if fuzzy error <= crisp error / 0, otherwise			
indep. variable	**description**	**Estimate**	**Stand. Err.**	
(intercept)	regression constant	0.2308	0.4972	
degree of uncertainty	WTP adjusted fuzzy set width	-0.6912	0.6219	
asymmetry	relative fuzzy set mark-up – relative mark-down	**4.9820**	1.8639	**
uncertainty & asymmetry	interaction term (uncertainty & asymmetry)	**-3.1301**	1.3919	*
WTP	summed up middle value of fuzzy set	-0.0002	0.0002	
interdependency	average mark-ups / mark-downs	-0.6260	0.4498	
technological knowl.	1, if 4 or 5 answers correct / 0, otherwise	0.2311	0.2331	
informed	1, if purchased recently or intend to purchase / 0, otherwise	0.0491	0.2813	
sex	1, if female/ 0, if male	0.0779	0.2848	
age	1, if 30 or older / 0, if younger than 30	0.2579	0.2954	
time	time spent for answering (in minutes)	0.0086	0.0125	
data sets: 151 AIC: 200.53	*signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*			

Experiment 2

In experiment 2, we simulated negotiations between a negotiation agent and a retailer. As we adjusted the experiment during the conduction phase, we just obtained 103 data sets. Altogether, the fuzzy negotiation outcome was chosen 433 times, the crisp 456 times, and 141 negotiation outcomes were assessed as indifferent. We performed a Wilcoxon signed rank test for experiment 2: the difference between fuzzy and crisp is not equal to zero with a p-value of 0.4642, i.e., there is no significant difference between the two models in terms of how well the negotiated contracts are compliant with the users' preferences.

The little difference of the models likely results from the fact that the negotiation problem is a relatively easy problem. As argued before, we omitted a lot of possible characteristics as well as attribute values to make the survey easier to handle for the respondents. Furthermore, the assumed negotiation setting is very simplifying. This simplification could be the reason why there is no significant difference between the outcomes. Potentially, further research with more complicated negotiation scenarios such as more attributes as well as attribute values or multilateral negotiation will yield more significant results. Especially in the case of multilateral negotiations, e.g., supply chain coordination, we expect that the fuzzy preference model is advantageous since the proposal acceptance quota is higher than in the crisp model. In the literature, it is shown that higher acceptance quotas can overcome local optima and be efficient in complex, nonlinear negotiations (Fink 2006).

Again, we conducted a probit regression for the negotiation (see Table 4 / Formula (4)). As we now consider prices as well, we included the price difference of the offers in the regression. The results show that in the second experiment technological knowledge and willingness to pay have a significant effect, whereby the willingness to pay has just a small influence (estimate) on the dependent variable. There is not sufficient significance for hypotheses H4a, H4b, and H4d which we reject then. The finding that technological knowledge improves the performance of the fuzzy preference model confirms hypothesis *H4c*. Technological knowledge represents domain knowledge in our setting. Presumably, test persons with high domain knowledge can express their subjectivity better and, therefore, more often choose the negotiation outcome of the fuzzy model.

Table 4. (Linear) Probit Regression for Experiment 2

dep. variable	**description**			
fuzzy negotiation	1, if selected fuzzy negotiation >= selected crisp negotiation / 0, otherwise			
indep. variable	**description**	**Estimate**	**Stand. Err.**	
(intercept)	regression constant	0.6548	0.6107	
degree of uncertainty	WTP adjusted fuzzy set width	-0.2239	0.8366	
asymmetry	relative fuzzy set mark-up – relative mark-down	0.3731	2.3222	
uncertainty & asymmetry	interaction term (uncertainty & asymmetry)	-0.2449	2.2982	
WTP	summed up middle value of fuzzy set	**-0.0004**	0.0002	.
interdependency	average mark-ups / mark-downs	0.2353	0.6509	
price	difference between prices of fuzzy & crisp outcomes	0.0004	0.0004	
technological knowledge	1, if 4 or 5 answers correct / 0, otherwise	**0.6940**	0.3075	*
informed	1, if purchased recently or intend to purchase / 0, otherwise	0.2595	0.3668	
sex	1, if female/ 0, if male	-0.2304	0.3305	
age	1, if 30 or older / 0, if younger than 30	0.4371	0.3664	
time	time spent for answering (in minutes)	-0.0102	0.0134	
data sets: 103 AIC: 145.59	*signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*			

Conclusions and Implications

In this work, we addressed two major problems in electronic negotiations, the modeling and elicitation of uncertain human preferences. We presented a new fuzzy set based preference model and a novel preference elicitation method for fuzzy preferences. We further evaluated our approaches empirically with two web-based experiments, for which we designed an e-commerce negotiation setting which involves laptop configurations. Our results show that the fuzzy preference model can project user choices more accurately than the crisp preference model, when the fuzzy sets are asymmetric, i.e., askew towards one side. The findings also indicate that the fuzzy model's performance is improved if the user has high domain knowledge. Moreover, the presented novel elicitation method appeared to be a suited method for the elicitation of fuzzy preferences. Furthermore, we showed that preferences are actually subject to uncertainty and that informed users, i.e., those who purchased a laptop recently, are less uncertain about their preferences. Moreover, we could verify that certain attributes are interdependent with other attributes. This finding is important because interdependencies can exacerbate negotiations and can represent a severe problem for the negotiation system design.

The main implication of our study is that the proposed fuzzy preference model and the preference elicitation method appear to be suited for the application in software agents. The agents' decisions can represent human decisions more realistically. We showed that domain knowledge can improve the fuzzy model's performance. This implies that a fuzzy negotiation system is particularly useful for management information system as business decision makers commonly have large domain knowledge. Since the proposal acceptance quota in the fuzzy preference model is higher than in the crisp model, we suppose, in accordance to the literature, that the model is suited to find agreements in conflicting situations. These situations in particular are given in multilateral negotiations.

Our study has also some limitations: First, the contract space is of much smaller size than in usual negotiation settings. Second, we used only triangular fuzzy sets and thus do not know whether other types of fuzzy sets are probably more appropriate. Third, we did not test uncertainty theories other than fuzzy set theory. Fourth, we did provide for multilateral settings. Future work will need to address the mentioned multilateral settings. For instance, the laptop configuration setting could be extended to find a laptop configuration which would be applied to a whole department. Further applications in other domains, e.g. in expert systems in supply chain coordination, are also imaginable. Also the enhancement of potential characteristics as well as attribute values and a more nuanced negotiation protocol should yield a more detailed analysis of the fuzzy preference model.

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