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A Survey of Decision Support Mechanisms for Negotiation

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Abstract. This paper introduces a dependency analysis and a categorization of conceptualized and existing economic decision support mechanisms for negotiation. The focus of our survey is on economic decision support mechanisms, although some behavioural support mechanisms were included, to recognize the important work in that area. We categorize support mechanisms from four different aspects: (i) economic versus behavioral decision support, (ii) analytical versus strategical support, (iii) active versus passive support and (iv) implicit versus explicit support. Our survey suggests that active mechanisms would be more effective than passive ones, and that implicit mechanisms can shield the user from mathematical complexities. Furthermore, we provide a list of existing economic support mechanisms.

Keywords: Negotiation support · Economic decision support · Survey

1 Introduction

Negotiation is part of our daily lives, informally at home or formally in matters of business. We negotiate to reach a consensus if we have a potential conflict of interests [19,43,65]. While some people are very good at negotiation, others have difficulty in reaching optimal outcomes and mostly end up with suboptimal outcomes [56,65]. *When to offer what* in negotiations, is the motivation of this paper and our research objective to support users with the aim to, if possible, obtain settlements that are 1) Pareto-optimal with respect to the preference profile of the negotiators, 2) good for the negotiator that negotiates according to these findings, and 3) that satisfy the additional constraints the user might set. Well-known additional constraints are social wellfare (ensuring that no negotiator is unduly disadvantaged), and timeliness.

Improved negotiation outcomes can be reached by training people before they enter the negotiation, delegating the negotiation to others, or supporting them

The authors are alphabetically sorted. They put the same effort.

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during the negotiation. For all of these options, one can either turn to other humans or to artificial intelligence, or to a combination of both. In this paper, the focus is on the use of artificial intelligence, see e.g., [8,33]. We follow Kersten and Lai [35] in using the term e-negotiation system (ENS) to cover the whole set of software systems for negotiation facilitation, support, and automation. We differentiate between analysis and decision support, and between Economic Decision Support (EDS) and Behavioral Decision Support (BDS) when discussing the literature on ENSs, following [22]. We found this differentiation useful as they form two dimensions to study; the need for support and the way mechanisms provide support. For example, the BDS side studies questions such as how to offer support on emotional aspects [15,49], and how to support humans in getting rapport with other human negotiators? On the EDS side belong challenges such as: What is an optimal strategy to reach optimal win-win solutions?

As we report in this paper, support mechanisms can serve as analytical mechanisms that inform both EDS and BDS mechanisms, target behavioral aspects, and/or target economic aspects. For example, the analysis of the economic aspects of a negotiator's preferences can be used to explain the emotional state of a negotiator, whereas a behavioral support mechanism advises the negotiator to make use of economic arguments in their conversation with other negotiators. When supporting or replacing humans by ENSs in experimental settings (cf. [9,21,35]), early successes of improved negotiation outcomes suggest that the EDS systems permit higher joint outcomes and more balanced contracts to be reached, while the BDS systems have a positive impact on negotiator attitudes. However, caution is needed as experimental results reported in Gettinger *et al.* [22] show that these expectations are not always met. In particular, their experiments did not support the hypotheses "More agreements/Better joint agreements/More fair agreements will be reached by negotiators provided with the EDS implemented in the eNSS $\mathcal{N}$egoisst than by negotiators for whom this type of support is not available". Furthermore, contrary to expectations, negotiators supported by a BDS system implemented in the VienNa system were more satisfied with the outcomes but less satisfied with the negotiation process. Given our expertise in system design, these findings lead to the thought that these unexpected (and unintended) results might be caused by the underlying design assumptions or the interaction effect between the mechanisms in the systems. In the remainder of this article, we zoom in on the economic support mechanisms for bidding. Note that we use the words of bidding and offering interchangeably.[1]

Our interest is in the design and engineering of AI technology for ENSs. Thus, our research questions derive from our observation that in the systems' performance, described in the literature, several of the unexpected (and unintended) results might be caused by underlying design assumptions and/or by interaction effects between the support mechanisms. In particular, we found two dimensions that struck us as important. The first is that each existing ENS system captures some negotiation expertise implicitly and others explicitly. In detail, negotiation

[1] In the automated negotiation literature the words *bid* and *bidding* are rather common, while in the general literature on negotiation the common word is *offer*.

knowledge or concepts can be exposed to the user implicitly; for example, the concept of utility is not useful for lay people, but can still implicitly be used in the system. However, for trained negotiators, utility is a well-known concept that can be discussed explicitly. We assume that implicit EDS mechanisms in the ENS system can increase the efficiency of the negotiation outcome by shielding the user from mathematical complexities. The second dimension is that some support mechanisms are actively pushed to the user, and some are passively available (can be pulled by the user). We expect that actively pushed support mechanisms are more effective than passive support mechanisms. Based on these considerations, we formulated the following two research questions.

- **RQ-1 Mechanisms:** What economic decision support mechanisms are available for bidding in ENSs?
- **RQ-2 Design:** What choices in the design of economic decision support mechanisms contribute to their success or failure?

Our research method is a combination of a literature study and an empirical study. For RQ-1, we survey and categorize the existing bidding support mechanisms in the literature and study their interdependencies. For RQ-2, we apply three methods: Firstly, we investigate the categorizations of ENSs as found in the literature, as they provide an overall design perspective of ENSs. Secondly, we focus on the economic decision support mechanisms of existing ENSs and finally, we identify the design choices for the existing ENSs and formulate hypotheses on what underlying design considerations potentially influence their effectiveness.

The structure of this paper is as follows. After mentioning the related work in Sect. 2, we review the literature on negotiation (support) systems and extract the bidding support mechanisms and their interdependencies offered by these systems in Sect. 3. The paper ends with conclusions and an outline for future research in Sect. 4.

2 Related Work

There is a wealth of research literature on negotiation, ranging from literature about human negotiations to the use of artificial intelligence to train, represent or support people in their negotiations. The history of research on providing computer support for negotiation is long, actually dating back to the 1960s, see, e.g., [20]. Worth mentioning is the Aspire system [37], which is one of the early negotiation support systems used for training negotiators. There is a steady stream of papers on these topics, with survey papers being published every couple of years, see Jelassi and Foroughi (1989) [27], Foroughi (1995) [20], Kersten and Lai [35], Wang [73], Marsa-Maestre *et al.* (2014) [45], and Baarslag (2017) *et al.* [8].

All research on ENS systems relies on insights from the rich literature on negotiation between human negotiators, see, e.g., Harvard's Business school with proponents such Fisher and Ury, e.g., [19], Lewicky [43], and Thompson [65], to name but a few. That literature is vital to understand the participants' behavior and the roles that they might have in a negotiation, be it as a negotiator, as a party represented by a negotiator, participant, as an advisor to a negotiator, or as mediator. Besides the human aspects and attitudes, there is also literature on the mathematical and economic aspects of negotiation, see, e.g., Raiffa and colleagues [56]. Additional insight comes from the literature that uses virtual agents to study human negotiation behavior, see e.g., [42,55]. Furthermore, virtual agents and feedback systems have been developed to train people in predetermined negotiation scenarios, see e.g., [23,28,47].

Reviews of the research on ENS systems show that there are many different aspects of negotiation for which support would be appreciated and that contributes to our overall objective [8,21,22,35,61], with early work dating back to the 1970s, see [51] and the literature survey in Sect. 3. Here, we provide classifications on types of support and an overview of the variety of key functions and tasks of software to benefit negotiations.

The proposal of Gettinger *et al.* [22] to differentiate between mechanisms for decision support and analytical mechanisms is the basis for the lay-out in Sect. 3, as analytical mechanisms can inform both EDS and BDS mechanisms. The dual use of analytical techniques also explains why the research fields of automated negotiation, see e.g., [6,33,38,59,68], and e-negotiation systems share important research challenges, namely how to deal with uncertainty about the negotiating parties, understanding the domain of negotiation, analyzing and understanding behavioral patterns of the negotiators, see e.g., [8]. The uncertainties negotiators face about the preferences and underlying concerns of the other negotiating parties have economic and emotional aspects. From an economic point of view, gathering more information about the profile of the other negotiators improves the possibilities of offering contracts that the others can accept. From an emotional point of view, reducing this uncertainty in the negotiator's mind potentially reduces stress which in turn enhances the capability of the negotiator to find integrative bargaining solutions. Such insights spur the research on opponent modeling (in particular preference modeling and estimating the opponent's reservation value), see, e.g., [3,6,33,52,68] and strategy recognition [40,74]. Creating a computational profile of the other negotiators is an essential step in other analytical tools, such as the determination of an estimated Pareto Optimal Frontier.

For the research and development of autonomous agents that support humans in negotiation or even autonomously fulfill the role of negotiator, more negotiation aspects need computer-readable formatting. In computer science and artificial intelligence, this is referred to as formal representations, e.g., referring to formal models, formal protocols, and ontologies. In the literature, negotiation process models are distinguished from negotiation protocols, see [39]. Negotiation process models describe the sequence of negotiation activities and phases. Negotiation protocols govern the processing and communication tasks, imposing restrictions and obligations on negotiation activities [18]. Work on formal protocols for negotiation makes it easier for agents to participate in negotiations, either in a supportive role or as automated negotiators, see e.g., [2,46,54,58].

Finally, the work that is most closely related to this paper is that of Chen *et al.* [13], Gettinger *et al.* [22], Schoop *et al.* [61], and Yuasa *et al.* [75,76], as discussed in more detail in the next section.

Formal models and ontologies are used to model the domain of negotiation. They are relevant for supporting the preparations for a negotiation, e.g., by using machine learning for market analysis and discovering patterns in the negotiating behavior of opponents in repeated negotiations. The research questions related to understanding behavioral patterns of negotiators are quite broad in themselves. Two example challenges are the following. Can we detect deception [24,48]? How can agents create rapport with people [12,53,67]? All these examples show that the challenge of developing ENS systems is a complex problem in which support mechanisms might enable other mechanisms and influence both economic decisions as well as behavior decisions. We give a few pointers to the automated negotiation literature: the literature of Automated Negotiating Agents Competition (ANAC) [33], team negotiation by Sanchez [59,60], negotiation for the Diplomacy game [29,30]. The negotiation handbook [46] recommends what negotiation mechanism to use for a given negotiation scenario. An overview of the current challenges in AI for negotiation is presented in [8].

3 Decision Support Mechanisms for Negotiations

We identify the analytical means and decision support (for BDS and EDS) needed for the economic decisions on 1) which concrete offers to make when and 2) whether or not to accept an offer or to end the negotiations without an agreement. We based our findings on literature surveys of the available categorisations of ENS systems. Note that we use the word bidding for what in other papers might be referred to as making offers and counteroffers.

Furthermore, we present an analysis of a literature survey focusing on EDS mechanisms for bidding support and advice. We considered analytical mechanisms that EDS mechanisms might need, and BDS mechanisms that rely on the same analytical mechanisms. Before presenting our survey results, we discuss the categorizations that can be found in the literature.

3.1 Categorizations and Classifications

Reviews of existing ENS systems show that there are many different aspects of negotiation that might be supported. Gettinger *et al.* [22] differentiate between **analysis** and **decision support** and between **economic** decision and **behavioral** decision support. Where analytical mechanisms inform the negotiator, decision support mechanisms provide strategic considerations; advising or critiquing on decisions. Finally, essential functions and tasks of software in e-negotiation should be considered [35,71].

Considering this, we decided to use two dimensions in our categorization. The first dimension entails the type of decisions, for which we follow Gettinger *et al.* [22]: **economic** versus **behavioral** decisions. The second dimension entails the mechanism's intended support of decisions: **analytical** or **strategical**. These dimensions turn out to be quite helpful in our analysis of the available mechanisms in the literature.

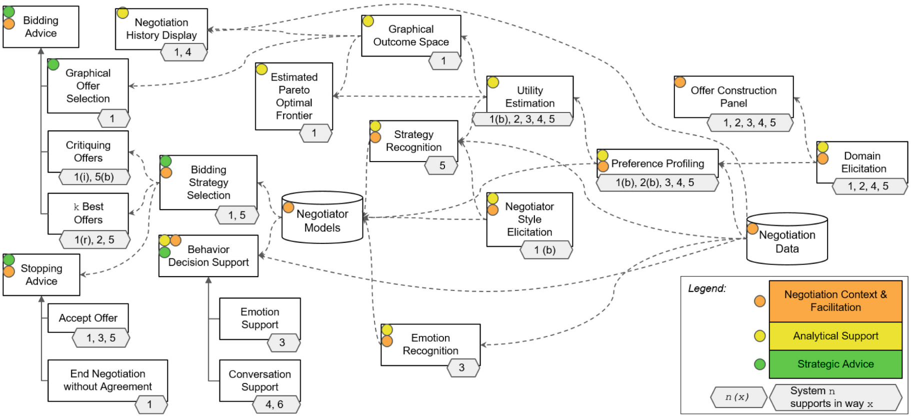
Systems playing a more active role on, e.g., making offer suggestions are still rare, as stated by Vetchera *et al.* in [72]. Here, eAgora [13] is mentioned as an exception, demonstrating important points for the design and engineering of ENS systems. For the design, a deliberate choice should be made to integrate the support mechanisms to provide passive or active support. We define a support mechanism to provide ***active support*** if it pro-actively pushes advice or information to the user in a timely manner. Similarly, we define a support mechanism to provide ***passive support*** if the support is available upon user request. In our survey, we looked for mechanisms that can provide analytical and/or strategic support and take into account whether that support is provided *actively* or *passively* (upon request). For engineering it shows that the problem formulation, modeling of the preferences, situation, and behavior of the negotiating parties are still difficult for humans and technology.

When studying the literature, we furthermore found, that the difference between providing explicit versus implicit support is essential. How ENS systems structure the negotiation process and organize the interfaces is based on expert negotiation knowledge. In that manner, the system ***implicitly*** supports the user by highlighting some aspects and takes care of other aspects that the system designers thought do not need the user's attention. For example, the $\mathcal{N}$egoisst interface reduces the negotiator's cognitive load for modeling their preferences and evaluating offers, and Pocket Negotiator (PN) first guides users in becoming aware of their own preferences before asking them to reflect on their opponents' preferences. ***Explicit*** support is visible in the negotiation and relational concepts that the system uses to present information or discuss negotiation aspects with the user. For instance, $\mathcal{N}$egoisst explicitly displays a utility tracking chart of the offers, EmoNeg provides explicit support on dealing with emotions, and PN explicitly asks for the users' interests in the negotiation. We conclude that design decision about providing implicit versus explicit support, and making it active or passive, are important for the effectiveness of support mechanisms.

We searched for components and mechanisms that correspond to the key functions and tasks software in ENSs as listed in [35], and also functions that come from the literature on automated negotiation [33], what to bid when, when to accept a bid, when to walk away, see [5]. The strategic support mechanisms we included in our survey are those that focus on EDS. That same literature also inspired our search for analytical support mechanisms. Analytical support is about providing information on the ongoing negotiation to the user on both economic and behavioral aspects. Economic analytical mechanisms include, for example, displaying how good the offers are for each negotiating party, preference profiling, which bids were made when (this is called the negotiation dance or history [56]), recognizing the opponent's strategy [40], providing information on where optimal outcomes can be found so that human negotiators can avoid sub-optimal outcomes. Behavior analytical mechanisms are, for example, emotion recognition. Note that all mechanisms for strategic advice rely directly or indirectly on analytical or other strategical mechanisms, while analytical mechanisms only rely on other analytical mechanisms.

In summary, we decided to use the following dimensions for our categorisation of the support mechanisms:

– **D1**: economic versus behavioral decision support
– **D2**: analytical versus strategical support
– **D3**: active versus passive support
– **D4**: implicit versus explicit support



x	Reading	#	System	Lit.
b	support refers to both opponent and user; without b only about the user	1	PN	[32]
i	support is implicitly available; without i it is explicitly available	2	FPJ	[20]
r	support is available upon request (passively); without r it is actively available	3	EmoNeg	[76]
p	support is only available in the post-settlement phase	4	$\mathcal{N}$egoisst	[62]
		5	eAgora	[13]
		6	VienNa	[16]

Fig. 1. Decision support mechanisms for negotiation

The survey results are presented in Fig. 1, in which the mechanisms are presented in rectangles, the ENSs using them are mentioned in the tags of the rectangles, the dependencies between the mechanisms are indicated by dotted arrows, and the color coding are classifications. In particular, following a dependency arrow from mechanism M to mechanism M' means that the results of M are used in M'. The color coding refers to dimension D2: analytical support (in yellow), strategic advice (in green), and whether the mechanism directly relies on the negotiation context information (in orange). The tags contain two types of information: a number referring to the ENS system and some additional information on the design choices according to dimensions D3 and D4. The tags are further explained in the legend of the figure.

In the remainder of this section, we explain each support mechanism in more detail and discuss whether and how it is used in the ENS systems we found. We explain more about the dependencies and the color labels in the diagram, for which we roughly follow the dependency arrows in the diagram (from right to left).

3.2 Existing Support Mechanisms

In this section, we present the list of support mechanisms from literature that underlie ENS systems in providing Economic Decision Support (EDS). However, as motivated in the Introduction and Sect. 3 some of these mechanisms also enable behavioral Decision Support mechanisms and we categorized these as ENS systems that (also) provide EDS. In comparison with Fig. 1, we roughly work from right to left, going from purely analytical support mechanisms to mechanisms for strategic advice.

To support the user, the ENS needs information about the negotiation context, the domain of negotiation, the user's preferences, if possible, similar information about the other negotiators, and about previous negotiations in similar contexts. The negotiation context is a broad container of topics not covered by the mechanisms discussed below. Information that is part of the negotiation context is, for example, the negotiation's deadline, the cultural background of the negotiators, and the emotional setting of the negotiation. A brief description of each support mechanism shown in Fig. 1 is provided below.

Domain Elicitation. Mechanisms for domain elicitation support the user to establish the issues (also called attributes) of the negotiation, i.e., the aspects to agree upon. Associated with each issue is a range of possible values that have to be identified, next to any dependencies between issues. An interactive user interface is the common form of support for this, occasionally supplemented with information from previous negotiations and from scraping the Internet.

Negotiation History Display and Negotiation Data. Negotiation History Display is a support mechanism that keeps track of and displays each player's offers during the negotiation. Its simplest form is just maintaining a list of past offers made by both participants. Our categorization depends on the more sophisticated variant; *Graphical Outcome Space*, depicting history graphically in the outcome space along with the (estimated) utilities of all negotiators. By analyzing the history of offers, users may understand their opponents' attitudes or strategies better. One of the first to discuss this is Raiffa [56], who called the sequence of exchanged offers; the negotiation dance. We broadened this by including past negotiations to learn more about the opponents' negotiation strategies and typical preference profiles per domain. Several versions are in existence, in PN, also for multi-lateral negotiations, see e.g., GENIUS and the newer GeniusWeb environments [44]. That data needs to be stored in a repository, called **Negotiation Data** in Fig. 1[2]. With the advance of machine learning algorithms, this category gains importance. It is part of the strategic advice and the other support mechanisms to timely share and exploit information extracted from the Negotiation History.

Offer Construction Panel. A basic mechanism, offered by all ENSs with EDS, that facilitates the user in constructing offers.

Preference Profiling. All support on what to offer requires information on the user's interests and preferences. Some systems in addition use similar information about the other negotiators. The essence of preference profiling is to discover what issues are more important than others, and per issue, which values are preferred. In case the system supports interest-based negotiation; also the underlying concerns and interests of the user (and the other negotiator) need to be established. There is a wealth of literature about preference elicitation, see, e.g., [10,14]. We found support for this phase in existing ENS systems, see e.g., [21,32,37]. Additionally, including other negotiators' preferences enables a system to provide more effective advice on what to offer and more insight on current and past offers made by the negotiators. Note that the user might actively do the profiling together with the artificial intelligence, by bringing in their knowledge about the opponent. However, even without human help, artificial intelligence techniques have been developed for modeling the opponent's preferences based on the opponent's offers; see [6] for a survey of such techniques. Presenting the preferences profiles to the user for easy inspection is also useful, see. e.g., [14].

Negotiator Style Elicitation. To most effectively advise the user on strategic decisions, the system would benefit from information on the usual style of the user regarding negotiation. For the system could deploy, e.g., a form of the Thomas-Kilmann conflict-handling mode instrument [64]. For example, it may not help to advise the user to play a hard-ball strategy (not making any concessions) if the user emotionally is not able to do so even if the user would agree that this would be smart in the current situation.

Utility Estimation. Mechanisms for Utility Estimation provide the (estimated) utility of (potential) offers from the different perspectives of the negotiating parties. This functionality is based on the system's mechanism for Preference Profiling and can support the user in making an informed decision about what to offer and what offers to accept or reject. Such a mechanism can be seen as a simple form of the more elaborate critiquing offers mechanism, as discussed below.

Estimated Pareto Optimal Frontier (EPOF). The mechanism for estimating the POF provides insights into which offers are thought to be Pareto optimal. Such a mechanism depends, of course on having preference profiles available of all negotiators. Typically, these negotiators' preference profiles are not available and have to be estimated by preference profiling mechanisms. Presenting the

[2] Note that the input comes from many of the mechanisms, but that these input links are not depicted in the figure.

EPOF can be done graphically for bilateral negotiations, but not for multilateral negotiations. In that case, listing the offers on the EPOF together with the estimated utilities for all negotiators might be an option.

Strategy Recognition. Mechanisms for Strategy Recognition aim to help the user recognize their opponent's strategy during negotiation so that user can adjust or refine his actions accordingly. Strategy Recognition for negotiation is still in its infancy. Currently, there have only been a few attempts in this direction; see, e.g., [40]. Maintaining the negotiation history is essential for strategy recognition.

Emotion Recognition. Mechanisms for Emotion Recognition can potentially be deployed to help users recognize their own and the other negotiators' emotional state. There is a wealth of literature on automated emotion recognition, which requires the use of multi-modal sensors to "read" the negotiators. However, using such sensors is ethically questionable. In the systems we found, emotion recognition is basically delegated to the user, whom via the user interface indicates the emotional state of the opponent [11,13]. Such mechanisms can be used to inform behavior decision support mechanisms.

Negotiator Models. We introduced the Negotiator Models repository that maintains all the data on the user and the other negotiators as acquired by the various mechanisms present in a system. From this repository, other mechanisms can extract information to support the user.

Graphical Outcome Space. A graphical representation of the possible outcomes of a bilateral negotiation that plots all possible offers on the space spanned by the utilities for both negotiators. This is only possible if the mechanism has access to the estimated utility functions for both negotiators and to the domain specification. It, therefore, depends directly on the Utility Estimation mechanism and indirectly on the mechanisms Preference Profiling and Domain Elicitation. If the EPOF is to be plotted, it also directly depends on the related mechanism. Having offers depicted in the graph provides easy insight into the use of that offer's efficiency. This would present a potential dependency on Negotiation History Display.

Bidding Strategy Selection. There already exist many competitive bidding and acceptance strategies, see e.g., [1,5,7,33,57]. Given these strategies, one would expect that negotiation support systems would also provide some strategic advice on what bidding strategy to select. So far, we have found no system that does so. Although eAgora [13] and PN let the users set and adjust their negotiation strategy.

Behavior Decision Support. In human negotiations interpersonal relationships are vital. The user may need emotional and conversational support to create rapport with the negotiation partner. There are some studies regarding how facial expressions affect the negotiation process. For instance, experiments have shown that human negotiators concede more when they are negotiating with a virtual agent having an angry facial expression than with an agent with a happy face

[49,70]. Similarly, in the study reported in [25], it is shown that dominant movements and emotional expressions are variables that provide higher scores during human agent negotiations. Yuasa *et al.* present a study in which their ENS system EmoNeg advises the participants on how to adapt their facial expressions to balance the emotions during negotiations. This form of emotional manipulation also enforces in human negotiators how important the negotiation atmosphere is. More information on these aspects can be found at, e.g., the Harvard Business School. The mechanism of EmoNeg is embedded in Fig. 1 under the name **Emotion Support**. Furthermore, mechanisms for **Conversation Support** are available in the $\mathcal{N}$egoisst and the VienNa ENS systems.

Graphical Offer Selection. The Graphical Offer Selection mechanism is related to the Offer Construction Panel mechanism as it also allows the user to construct an offer. However, the mechanism relies entirely on the Graphical Outcome Space mechanism. It allows the user to click on a point in that space, and its underlying offer is immediately constructed as a bid in the Offer Construction Panel. In PN this mechanism is implemented for the EPOF offers only.

Bidding Advice. Mechanisms that provide Bidding Advice, i.e., advice on what to offer or counteroffer, ideally have access to the negotiation context (e.g., to know the negotiation deadline or other constraints), and to the models of all negotiators; not just to the user's model. In particular, the mood and/or emotional states of the negotiators, information on their preference/utility profiles and their negotiation strategies. We found two specific forms of bidding advice in the ENS systems, namely **Critiquing Offers** and k **Best Offers**. **Critiquing Offers** as discussed and used in eAgora [13] is a mechanism that pro-actively critiques offers received from the opponent (e.g., to reject an offer) or that the user plans to make (e.g., that the user is conceding too much) based on a set of critiquing rules. k **Best Offers** is a mechanism that suggests k best alternative offers to make based on the selected strategies and the preferences. Variation is in terms of the parameter k, and whether or not only the user's strategy and preferences are taken into account (user-oriented), or also those of the other negotiators (all-oriented). The mechanism is used in eAgora [13] ($k = 5$, user-oriented), FPJ [21] ($k = 3$, user-oriented), and PN [32] ($k = 1$, all-oriented).

Stopping Advice. We found two explicit mechanisms on stopping the negotiation; **Accept Offer** and **End Negotiation without Agreement**. We found three systems that provide the Accept Offer mechanism, i.e., FPJ [21], eAgora [13], and PN [32]. For an overview of strategies for accepting bids, see [7]. Strategic advice on when to walk away from the negotiation without an agreement is discussed in [34]. Both the advice to accept the offer or to end the negotiation without an agreement can be encountered in PN.

3.3 Available Decision Support Systems for Negotiation

Given the long history of the field of ENSs one might expect fully fledged ENSs readily available to the interested negotiator. However, to date, our search for systems that offer active and concrete support during potentially real negotiations on arbitrary domains and for which peer-reviewed scientific papers are available, returned only the following systems[3]: **FPJ** [20], **EmoNeg** [76], **Aspire** [37], **$\mathcal{N}$egoisst** [62], **VienNa** [16], **eAgora** [13], and **Pocket Negotiator (PN)** [32]. These systems play a major role in our survey and in our resulting diagram, see Fig. 1.

The FPJ System. A negotiation support system with a long history is that of Foroughi, Perkins, and Jelassi ([20,21]) that offers mechanisms they call Contract Point Evaluator and Decision Tool. Yet, we could not find a current version of the tool. The Decision Tool estimated the point structure of the other negotiating party, which is why the mechanism *Preference Profiling* in Fig. 1 is tagged with a "2" and the parameter "b" indicating a preference structure for both negotiating parties. The Decision tool generated all possible outcomes and ranked them in descending order of the joint utilities (summation), which is why the *Utility Estimation* mechanism has the tag 2(b) as well. In their system, the three bids with the highest joint outcome were displayed to the user, which is a form of the *k Best Offers* ($k = 3$) mechanism. Note that their mechanism was implemented as an active mechanism with the implicit aspect of the suggestion to pick from the three best options. The Contract Point Calculator in [20] allowed people to enter an offer, which is a form of the *Offer Construction Panel*. The Contract Point Calculator calculated the user's score (utility) for that offer, but not that of the opponent. In their experiments, Foroughi *et al.* varied on the competitiveness of the bargaining task, and they showed that their system improved negotiation outcomes and user satisfaction [21].

The EmoNeg System. The EmoNeg system by Yuasa *et al.* [76] provides bidding advice on the height of the offer based on the user's utility function, which means the system has a form of *Utility Estimation* but only from the user's perspective; thus tagged with a "3" without the parameter "b". The paper presents the system for negotiation within the game"Monopoly" and makes no mention of providing support for domain elicitation. However, there is an *Offer Construction Panel*. EmoNeg specialises on *emotion support* on the basis of Newcomb's ABX model [50] to advice humans during negotiations on their next move. The rule-based mechanism for this is based on [66], and by asking the user to perform the task of *Emotion Recognition* from the other negotiator's facial expression.

The $\mathcal{N}$egoisst System. $\mathcal{N}$egoisst [61,62] is an ENS system that provides decision support, communication support, and document management as depicted in Fig. 2. In this paper, we only focus on its decision-support elements; however, we tagged $\mathcal{N}$egoisst on the Behavior Decision Support mechanism *Conversation Support*. $\mathcal{N}$egoisst provides support to the user for preference elicitation and utility estimation, and it displays and stores the negotiation history, as tagged

[3] Note that FPJ and EmoNeg are names given to these systems by the authors of the current paper.

accordingly in Fig. 1. We interpret the way that $\mathcal{N}$egoisst documents and processes the information, the messages exchanged between the negotiators, and the use of the informal "green" and formal "red" workspaces as a form of *Domain Elicitation* mechanism. Messaging is based on Speech Act Theory [63]. The message editor is a form of *Offer Construction Panel* The utility estimation of offers and counteroffers is estimated based on the preference elicitation process giving a utility range for partial offers. The *Negotiation History Display* mechanism shows the estimated utility of previous offers concerning only the user's own preferences. Note that $\mathcal{N}$egoisst has storage of Negotiation Data and Negotiator Models.

Fig. 2. Bidding interface of $\mathcal{N}$egoisst [61]

The eAgora System. eAgora [13] is an ENS system for multi-issue negotiations in e-marketplaces. The eAgora agent generates and actively pushes a set of attractive alternative offers to the user (*k Best Offers*, with $k = 5$), actively pushes critique on offers that the user contemplates to submit, and on offers received by the opponent (*Critiquing Offers*) as seen in Fig. 3. eAgora implements *Strategy Recognition* a fuzzy assessment of the concessions of the opponent measured according to the user's utility function. The *Bidding Strategy Selection* allows the user to select "competitive", "collaborative", "compromising", or "accommodating". Furthermore, eAgora implements forms of *Domain Elicitation*, *Offer Construction Panel*, *Preference Profiling* (for the user only), *Utility Estimation* (for the user only), *Strategy Recognition*, and *Accept Offer*, see Fig. 1.

The authors motivate actively pushing advice by stating that users do not need advanced technical or decision analytical skills. Presenting a set of top alternatives instead of just one is motivated by two arguments. First, the user

(a) Offer Construction in eAgora (b) Critiquing by eAgora

Fig. 3. The user interfaces of eAgora [13]

preference model is only an approximation of the user's true preferences, and providing a set of alternatives gives the negotiator a better idea of what good or satisfying offers are like.

The VienNa System. VienNa [16,17] is a mediation support system that collects information on how flexible negotiators are on the negotiation issues and process by using an e-survey. The flexibility score is presented in a grid, see Fig. 4. The system provides interaction advice regarding integrative agreements, fairness, information exchange, and fractionation of issues. Their interaction advice is a facilitation type of support, tagged as the *Conversation Support* mechanism in Fig. 1.

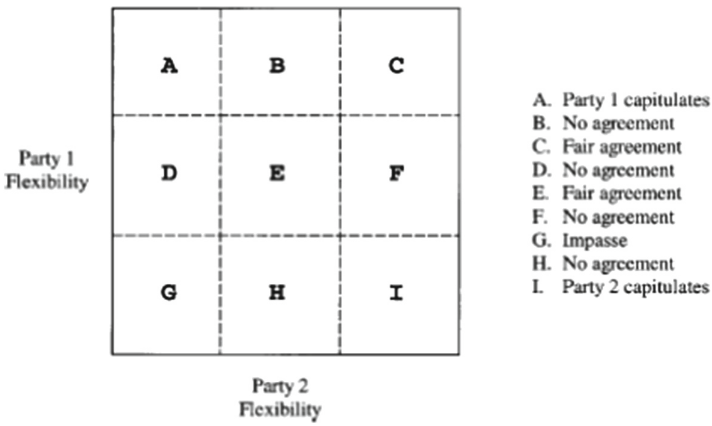


Fig. 4. Qualitative analysis of flexibility in VienNa [17]

Pocket Negotiator. The Pocket Negotiator [32] (PN) provides guidance throughout the negotiation process. In this article, we focus on its EDS aspects in the bidding phase. The PN provides the following mechanisms, see Fig. 5:

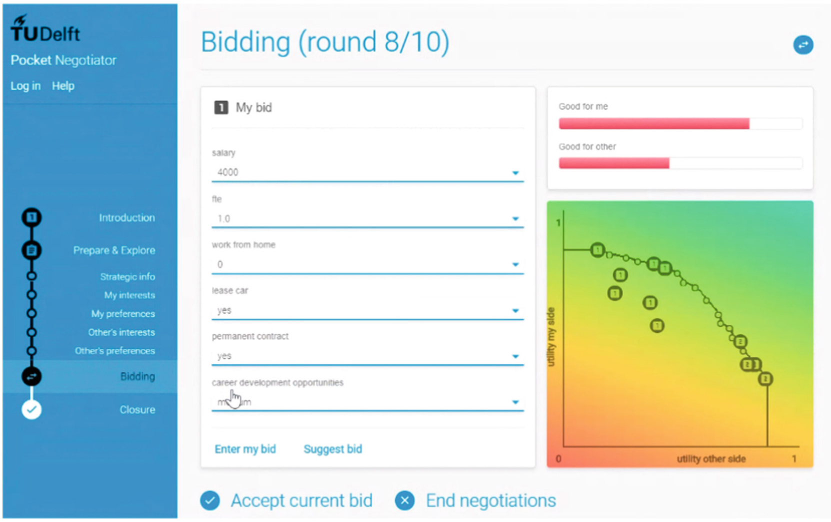


Fig. 5. Bidding interface of the Pocket Negotiator

Domain Elicitation: PN has an interest-based domain editor for modeling multi-issue bilateral domains.

Offer Construction Panel: A GUI with pull-down menu's per issue to select values.

Preference Profiling: PN provides panels for interest-based preference profiling. Users are guided through profiling their own, as well as in *estimating* their opponent's preferences.

Utility Estimation: Based on the preference profiles PN automatically creates utility functions for both the user and the other negotiator, see the red bars in Fig. 5.

Negotiator Style Elicitation: A mini questionnaire helps users reflect on their own negotiation style and expertise and that of the other negotiator.

Graphical Outcome Space: In the right of Fig. 5 the axes represent utility (y-axis = user, x-axis = other negotiator). The mechanism uses the (estimated) utility functions to plot offers as dots in the space. The colour of the background indicates efficiency: from green (efficient) via orange to red (inefficient).

Negotiation History Display: The offers made by both negotiators are logged and presented as dots in the *Graphical Outcome Space* on the right of Fig. 5. This provides the user with insights in the progress of the negotiation. The user can hover over these offers to see their content in a pop-up window.

EPOF: This mechanism uses the (estimated) utility functions of the negotiators to compute the EPOF, and displays these offers as dots in the *Graphical Outcome Space* on the right of Fig. 5. The EPOF construction depends on the results of the *Estimated Utility* mechanism, which in turn relies on the *Preference Profiling* mechanism and on the *Domain Elicitation* mechanism.

Graphical Offer Selection: The user can click on dots of the EPOF in the *Graphical Outcome Space* as presented on the right of Fig. 5. Selected offers are copied immediately to the *Offer Construction Panel*. Hovering over a dot, causes the contents to be displayed.

Strategy Selection: Users can select the agent and accompanying strategy to support them with bidding and stopping advice. PN offers a range of strategies to pick from, including Tit-for-Tat, Hard Headed, Optimal Conceder, and Deniz, based on the literature [26,31,33,41].

Critiquing Offers: PN provides an implicit form of critiquing offers by depicting the user's utility and that of the opponent through red bars, on the right of Fig. 5. This mechanism depends on the mechanism *Utility Estimation*.

k ***Best Offer***: PN provides this mechanism for $k = 1$ passively; in the tag this is indicated by the parameter "r" that stands for "upon request". The mechanism is accessible to the user by clicking on the **Suggest Bid** button (at the bottom of Fig. 5).

Stopping Advice: PN provides active variants of the mechanisms *Accept Offer* and *End Negotiation without Agreement*. The actual advice comes from the supporting agent selected by the user.

Repositories: PN logs the negotiation sessions in a Negotiation Data repository, containing also domain models, preference profiles, negotiator models of both the user and the other negotiator, and a repository of negotiation support agents.

To emphasize, PN users can create offers in three ways: by selecting a value for each issue in the *Offer Construction Panel*, by clicking on offers on the EPOF in the *Graphical Outcome Space*, or by asking for a suggestion ("Suggest bid").

In summary, PN provides passive economic bidding advice with some implicit and nudging aspects. The design choice to make only offers on the EPOF clickable, gently encourages (nudges) users not to make Pareto sub-optimal bids. The *k Best Offers* mechanism is passive as the user has to request it by clicking on the "Suggest Bid" button. The support agent selected by the user actively provides stopping advice to the user.

Other Related Systems. We do not want to end this section without referring to the other excellent systems in the field of negotiation and negotiation support. The Aspire system [37] is one of the early negotiation support systems used for training negotiators. Aspire provides advice to negotiators, but not through generating offers or critiquing offers. The support is text-based, and the system tries to teach negotiators what effect their explanations of their motivation behind their bids might have on their opponents. It is, however, not easy to adapt the system to new negotiation domains and thus not easy to use for real negotiations in changing domains.

The Shaman system [36] is a framework for the construction and operation of heterogeneous systems enabling business interactions such as auctions and negotiations between software and human agents across those systems. It does not provide support mechanisms of its own, but integrates them.

Looking a bit further afield, we recommend the reader also to consider the Social agent for Advice Provision (SAP) [4]. SAP is an agent that models human choice selection using hyperbolic discounting and samples the model to infer the best weights for its social utility function. In contrast to ENS systems, the SAP agent argues with its human opponent to convince the opponent to take actions that are mutually beneficial to the system and the human. SAP explicitly reasons about the trade-offs between the costs to both participants in the selection process based on a social weight. Both the work by [4,69] is relevant for negotiation support systems, as it will optimize the advice that can be given to the human user. One might adapt other ENS systems to advise the human negotiator on potential trade-offs.

4 Conclusions and Future Work

This paper introduces a categorization of potential and existing economic decision support (EDS) mechanisms. The study focused on analytical support and strategic advice. Our survey of the literature revealed that mechanisms can be integrated into the e-Negotiation Support (ENS) systems to actively (push) or passively (available upon request) provide support to the user. Furthermore, the mechanisms can explicitly or implicitly refer to negotiation concepts and knowledge. In literature, we found evidence that the use of implicit knowledge can be beneficial for the user as it can shield the user from mathematical complexities.

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References

1. Aydoğan, R., et al.: Challenges and main results of the automated negotiating agents competition (ANAC) 2019. In: The Seventh International Conference on Agreement Technologies. Greece (2020)

2. Aydoğan, R., Festen, D., Hindriks, K.V., Jonker, C.M.: alternating offers protocols for multilateral negotiation. In: Fujita, K., et al. (eds.) Modern Approaches to Agent-based Complex Automated Negotiation. SCI, vol. 674, pp. 153–167. Springer, Cham (2017). https://doi.org/10.1007/978-3-319-51563-2_10
3. Aydogan, R., Yolum, P.: Learning opponent's preferences for effective negotiation: an approach based on concept learning. Auton. Agents Multi Agent Syst. **24**(1), 104–140 (2012)
4. Azaria, A., Rabinovich, Z., Kraus, S., Goldman, C.V., Gal, Y.: Strategic advice provision in repeated human-agent interactions. Inst. Adv. Comput. Stud. Univ. Maryland **1500**(20742), 23 (2012)
5. Baarslag, T., Gerding, E.H., Aydoğan, R., Schraefel, M.C.: Optimal negotiation decision functions in time-sensitive domains. In: 2015 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology (WI-IAT). vol. 2, pp. 190–197 (December 2015). https://doi.org/10.1109/WI-IAT.2015.161
6. Baarslag, T., Hendrikx, M.J.C., Hindriks, K.V., Jonker, C.M.: Learning about the opponent in automated bilateral negotiation: a comprehensive survey of opponent modeling techniques. Auton. Agent. Multi-Agent Syst. **30**(5), 849–898 (2015). https://doi.org/10.1007/s10458-015-9309-1
7. Baarslag, T., Hindriks, K.V.: Accepting optimally in automated negotiation with incomplete information. In: Proceedings of the 2013 International Conference on Autonomous Agents and Multi-Agent Systems, pp. 715–722 (2013)
8. Baarslag, T., Kaisers, M., Gerding, E., Jonker, C., Gratch, J.: When will negotiation agents be able to represent us? the challenges and opportunities for autonomous negotiators. In: Proceedings of the Twenty-sixth International Joint Conference on Artificial Intelligence, pp. 4684–4690 (Aug 2017). 10.24963/ijcai.2017/653
9. Bosse, T., Jonker, C.M.: Human vs. computer behavior in multi-issue negotiation. In: Rational, Robust, and Secure Negotiation Mechanisms in Multi-Agent Systems (RRS'05), pp. 11–24. IEEE (2005)
10. Boutilier, C., Brafman, R.I., Domshlak, C., Hoos, H.H., Poole, D.: CP-nets: A tool for representing and reasoning withconditional ceteris paribus preference statements. J. Artif. Intell. Res. **21**, 135–191 (2004)
11. Broekens, J., Harbers, M., Brinkman, W.-P., Jonker, C.M., Van den Bosch, K., Meyer, J.-J.: Virtual reality negotiation training increases negotiation knowledge and skill. In: Nakano, Y., Neff, M., Paiva, A., Walker, M. (eds.) IVA 2012. LNCS (LNAI), vol. 7502, pp. 218–230. Springer, Heidelberg (2012). https://doi.org/10.1007/978-3-642-33197-8_23
12. Cassell, J., Bickmore, T.: Negotiated collusion: modeling social language and its relationship effects in intelligent agents. User Model. User-ADAP. Inter. **13**(1–2), 89–132 (2003)
13. Chen, E., Vahidov, R., Kersten, G.E.: Agent-supported negotiations in the e-marketplace. Int. J. Electron. Bus. **3**(1), 28–49 (2005)
14. Chen, Y., Qian, J., Wang, J., Xia, L., Zahavi, G.: Opra: an open-source online preference reporting and aggregation system. arXiv preprint arXiv:2005.13714 (2020)
15. Dehghani, M., Carnevale, P.J., Gratch, J.: Interpersonal effects of expressed anger and sorrow in morally charged negotiation. Judg. Decis Mak. **9(**2) (2014)
16. Druckman, D., Druckman, J.N., Arai, T.: e-mediation: evaluating the impacts of an electronic mediator on negotiating behavior. Group Decis. Negot. **13**(6), 481–511 (2004)
17. Druckman, D., Ramberg, B., Harris, R.: Computer-assisted international negotiation: a tool for research and practice. Group Decis. Negot. **11**(3), 231–256 (2002)

18. Faratin, P., Sierra, C., Jennings, N.: Negotiation decision functions for autonomous agents. Robot. Auton. Syst. **24**(3), 159–182 (1998)
19. FISHER, R., William, L.: Getting to Yes. Penguin Group, New York (1981)
20. Foroughi, A., Perkins, W., Jelassi, T.: An empirical study of an interactive, session-oriented computerized negotiation support system (NSS). Group Decis. Negotiat. **4**, 485–512 (1995). https://doi.org/10.1007/BF01409712
21. Foroughi, A., Perkins, W.C., Hershauer, J.C.: A study of asymmetrical decision support in computerized negotiation support systems (NSS). Glob. Bus. Fin. Rev. **20**(1), 25–42 (2015)
22. Gettinger, J., et al.: Impact of and interaction between behavioral and economic decision support in electronic negotiations. In: Hernández, J.E., et al. (eds.) Decision Support Systems - Collaborative Models and Approaches in Real Environments, pp. 151–165. Springer, Berlin Heidelberg (2012)
23. Gratch, J., DeVault, D., Lucas, G.: The benefits of virtual humans for teaching negotiation. In: Traum, D., Swartout, W., Khooshabeh, P., Kopp, S., Scherer, S., Leuski, A. (eds.) IVA 2016. LNCS (LNAI), vol. 10011, pp. 283–294. Springer, Cham (2016). https://doi.org/10.1007/978-3-319-47665-0_25
24. Gratch, J., Nazari, Z., Johnson, E.: The misrepresentation game: how to win at negotiation while seeming like a nice guy. In: Proceedings of the 2016 International Conference on Autonomous Agents & Multiagent Systems, pp. 728–737. IFAAMAS (2016)
25. Gratch, J., DeVault, D., Lucas, G.: The benefits of virtual humans for teaching negotiation. In: Traum, D., Swartout, W., Khooshabeh, P., Kopp, S., Scherer, S., Leuski, A. (eds.) IVA 2016. LNCS (LNAI), vol. 10011, pp. 283–294. Springer, Cham (2016). https://doi.org/10.1007/978-3-319-47665-0_25
26. Hindriks, K., Tykhonov, D.: Opponent modelling in automated multi-issue negotiation using bayesian learning. In: Proceedings of the 7th International Conference on Autonomous Agents and Multi-Agent Systems, pp. 331–338 (2008)
27. Jelassi, M.T., Foroughi, A.: Negotiation support systems: an overview of design issues and existing software. Decis. Support Syst. **5**(2), 167–181 (1989)
28. Johnson, E., Lucas, G., Kim, P., Gratch, J.: Intelligent tutoring system for negotiation skills training. In: Isotani, S., Millán, E., Ogan, A., Hastings, P., McLaren, B., Luckin, R. (eds.) AIED 2019. LNCS (LNAI), vol. 11626, pp. 122–127. Springer, Cham (2019). https://doi.org/10.1007/978-3-030-23207-8_23
29. de Jonge, D., Baarslag, T., Aydoğan, R., Jonker, C., Fujita, K., Ito, T.: The challenge of negotiation in the game of diplomacy. In: Lujak, M. (ed.) Agreement Technologies, pp. 100–114. Springer International Publishing, Cham (2019). https://doi.org/10.1007/978-3-030-17294-7_8
30. de Jonge, D., Sierra, C.: D-Brane: a diplomacy playing agent for automated negotiations research. Appl. Intell. **47**(1), 158–177 (2017). https://doi.org/10.1007/s10489-017-0919-y

31. Jonker, C.M., Aydoğan, R.: Deniz: a robust bidding strategy for negotiation support systems. In: Ito, T., Zhang, M., Aydoğan, R. (eds.) ACAN 2018. SCI, vol. 905, pp. 29–44. Springer, Singapore (2021). https://doi.org/10.1007/978-981-15-5869-6_3
32. Jonker, C.M., et al.: An introduction to the pocket negotiator: a general purpose negotiation support system. In: Criado Pacheco, N., Carrascosa, C., Osman, N., Julián Inglada, V. (eds.) EUMAS/AT -2016. LNCS (LNAI), vol. 10207, pp. 13–27. Springer, Cham (2017). https://doi.org/10.1007/978-3-319-59294-7_2
33. Jonker, C.M., Aydoğan, R., Baarslag, T., Fujita, K., Ito, T., Hindriks, K.V.: Automated negotiating agents competition (anac). In: AAAI, pp. 5070–5072 (2017)
34. Jonker, C.M., Robu, V., Treur, J.: An agent architecture for multi-attribute negotiation using incomplete preference information. Auton. Agent. Multi-Agent Syst. **15**(2), 221–252 (2007)
35. Kersten, G., Lai, H.: Negotiation support and e-negotiation systems: an overview. Group Decis. Negot. **16**, 553–586 (2007)
36. Kersten, G.E., Kowalczyk, R., Lai, H., Neumann, D., Chhetri, M.B.: Shaman: software and human agents in Multiattribute auctions and negotiations. In: Gimpel, H., Jennings, N.R., Kersten, G.E., Ockenfels, A., Weinhardt, C. (eds.) Negotiation, Auctions, and Market Engineering. LNBIP, vol. 2, pp. 116–149. Springer, Heidelberg (2008). https://doi.org/10.1007/978-3-540-77554-6_9
37. Kersten, G.E., Lo, G.: Aspire: an integrated negotiation support system and software agents for e-business negotiation. Int. J. Internet Enterpr. Manag. **1**(3), 293–315 (2003)
38. Keskin, M.O., Çakan, U., Aydoğan, R.: Solver Agent: Towards Emotional and Opponent-Aware Agent for Human-Robot Negotiation. In: Proceedings of the 20th International Conference on Autonomous Agents and MultiAgent Systems, pp. 1557–1559. AAMAS '2021 (2021)
39. Kim, J.B., Segev, A.: A framework for dynamic ebusiness negotiation processes. In: EEE International Conference on E-Commerce, pp. 84–91. IEEE (2003)
40. Koeman, V.J., Hindriks, K.V., Gratch, J., Jonker, C.M.: Recognising and explaining bidding strategies in negotiation support systems. In: Proceedings of the 18th International Conference on Autonomous Agents and Multi-Agent Systems, pp. 2063–2065 (2019)
41. van Krimpen, T., Looije, D., Hajizadeh, S.: Hardheaded. In: Complex Automated Negotiations: Theories, Models, and Software Competitions, pp. 223–227. Springer, Cham (2013). https://doi.org/10.1007/978-3-642-30737-9_17
42. Lee, M., Lucas, G., Mell, J., Johnson, E., Gratch, J.: What's on your virtual mind?: mind perception in human-agent negotiations. In: Proceedings of the 19th ACM International Conference on Intelligent Virtual Agents, pp. 38–45 (2019)
43. Lewicki, R.J., Saunders, D.M., Barry, B., Minton, J.W.: Essentials of Negotiation. McGraw-Hill, Boston, MA (2003)
44. Lin, R., Kraus, S., Baarslag, T., Tykhonov, D., Hindriks, K., Jonker, C.M.: Genius: an integrated environment for supporting the design of generic automated negotiators. Comput. Intell. **30**(1), 48–70 (2014)
45. Marsa-Maestre, I., Klein, M., Jonker, C.M., Aydoğan, R.: from problems to protocols: Towards a negotiation handbook. Decision Supp. Syst. **60,** 39–54 (2014), automated Negotiation Technologies and their Applications
46. Marsa-Maestre, I., Klein, M., Jonker, C.M., Aydoğan, R.: From problems to protocols: towards a negotiation handbook. Decis. Support Syst. **60**, 39–54 (2014)

47. Mell, J., Gratch, J., Baarslag, T., Aydoğan, R., Jonker, C.M.: Results of the first annual human-agent league of the automated negotiating agents competition. In: Proceedings of the 18th International Conference on Intelligent Virtual Agents, pp. 23–28 (2018)
48. Mell, J., Lucas, G.M., Mozgai, S., Gratch, J.: The effects of experience on deception in human-agent negotiation. J. Artif. Intell. Res. **68**, 633–660 (2020)
49. de Melo, C.M., Carnevale, P., Gratch, J.: The effect of expression of anger and happiness in computer agents on negotiations with humans. In: The 10th International Conference on Autonomous Agents and Multi-Agent Systems, pp. 937–944 (2011)
50. Newcomb, T.M.: An approach to the study of communicative acts. Psychol. Rev. **60**(6), 393 (1953)
51. Nyhart, J.D., Gltner, C.: Computer Models as Support for Complex Negotiations. Palala Press (2015)
52. Oshrat, Y., Lin, R., Kraus, S.: Facing the challenge of human-agent negotiations via effective general opponent modeling. In: AAMAS, vol. 1. pp. 377–384. IFAAMAS (2009)
53. Planken, B.: Managing rapport in lingua franca sales negotiations: a comparison of professional and aspiring negotiators. Engl. Specif. Purp. **24**(4), 381–400 (2005)
54. Ponsatí, C., Sákovics, J.: Rubinstein bargaining with two-sided outside options. Econ. Theor. **11**(3), 667–672 (1998)
55. Prajod, P., Al Owayyed, M., Rietveld, T., van der Steeg, J.J., Broekens, J.: The effect of virtual agent warmth on human-agent negotiation. In: Proceedings of the 18th International Conference on Autonomous Agents and MultiAgent Systems, pp. 71–76 (2019)
56. Raiffa, H., Richardson, J., Metcalfe, D.: Negotiation Analysis: The Science and Art of Collaborative Decision Making. Belknap Press (2002)
57. Razeghi, Y., Yavuz, O., Aydoğan, R.: Deep reinforcement learning for acceptance strategy in bilateral negotiations. Turkish J. Electr. Eng. Comput. Sci. **28**, 1824–1840 (2020)
58. Rosenschein, J.S., Zlotkin, G.: Rules of Encounter: Designing Conventions for Automated Negotiation Among Computers. MIT Press, Cambridge (1994)
59. Sanchez-Anguix, V., Aydoğan, R., Julian, V., Jonker, C.M.: Intra-team strategies for teams negotiating against competitor, matchers, and conceders. In: Marsa-Maestre, I., Lopez-Carmona, M.A., Ito, T., Zhang, M., Bai, Q., Fujita, K. (eds.) Novel Insights in Agent-based Complex Automated Negotiation. SCI, vol. 535, pp. 3–22. Springer, Tokyo (2014). https://doi.org/10.1007/978-4-431-54758-7_1
60. Sanchez-Anguix, V., Aydoğan, R., Julian, V., Jonker, C.: Unanimously acceptable agreements for negotiation teams in unpredictable domains. Electron. Commer. Res. Appl. **13**(4), 243–265 (2014)
61. Schoop, M., van Amelsvoort, M., Gettinger, J., Koerner, M., Koeszegi, S.T., van der Wijst, P.: The interplay of communication and decisions in electronic negotiations: communicative decisions or decisive communication? Group Decis. Negot. **23**(2), 167–192 (2014)
62. Schoop, M., Jertila, A., List, T.: Negoisst: a negotiation support system for electronic business-to-business negotiations in e-commerce. Data Knowl. Eng. **47**(3), 371–401 (2003)
63. Searle, J.R., Kiefer, F., Bierwisch, M., et al.: Speech Act Theory and Pragmatics, vol. 10. Springer, Dordrecht (1980). https://doi.org/10.1007/978-94-009-8964-1
64. Thomas, K.W.: Thomas-kilmann conflict mode. TKI Profile and Interpretive Report pp. 1–11 (2008)

65. Thompson, L.: The Mind and Heart of the Negotiator, 3rd edn. Prentice Hall Press, Upper Saddle River (2000)
66. Thompson, L., Medvec, V.H., Seiden, V., Kopelman, S.: Poker face, Smiley Face, and Rant 'n'rave: Myths and Realities About Emotion in Negotiation. Blackwell handbook of social psychology: Group processes, pp. 139–163 (2001)
67. Thompson, L., Nadler, J.: Negotiating via information technology: theory and application. J. Soc. Issues **58**(1), 109–124 (2002)
68. Tunalı, O., Aydoğan, R., Sanchez-Anguix, V.: Rethinking frequency opponent modeling in automated negotiation. In: An, B., Bazzan, A., Leite, J., Villata, S., van der Torre, L. (eds.) PRIMA 2017. LNCS (LNAI), vol. 10621, pp. 263–279. Springer, Cham (2017). https://doi.org/10.1007/978-3-319-69131-2_16
69. Vahidov, R., Kersten, G., Saade, R.: An experimental study of software agent negotiations with humans. Decis. Supp. Syst. **66**, 135–145 (2014).https://doi.org/10.1016/j.dss.2014.06.009, https://www.sciencedirect.com/science/article/abs/pii/S0167923614001833
70. Van Kleef, G.A., De Dreu, C.K., Manstead, A.S.: The interpersonal effects of anger and happiness in negotiations. J. Pers. Soc. Psychol. **86**(1), 57 (2004)
71. Vetschera, R.: Group decision and negotiation support-a methodological survey. Oper. Res.-Spekt. **12**(2), 67–77 (1990)
72. Vetschera, R., Filzmoser, M., Mitterhofer, R.: An analytical approach to offer generation in concession-based negotiation processes. Group Decis. Negot. **23**(1), 71–99 (2014)
73. Wang, Z., Lim, J., Guo, X.: Negotiator satisfaction in NSS-facilitated negotiation. Group Decis. Negot. **19**(3), 279–300 (2010)
74. Williams, C.R., Robu, V., Gerding, E.H., Jennings, N.R.: Using gaussian processes to optimise concession in complex negotiations against unknown opponents. In: Walsh, T. (ed.) IJCAI 2011, Proceedings of the 22nd International Joint Conference on Artificial Intelligence, Barcelona, Catalonia, Spain, July 16–22, 2011. pp. 432–438. IJCAI/AAAI (2011)
75. Yuasa, M., Yasumura, Y., Nitta, K.: Giving advice in negotiation using physiological information. In: Proceedings of the 2000 International Conference on Systems, Man and Cybernetics, vol. 1, pp. 248–253 (October 2000)
76. Yuasa, M., Yasumura, Y., Nitta, K.: A negotiation support tool using emotional factors. In: Proceedings Joint 9th IFSA World Congress and 20th NAFIPS International Conference, pp. 2906–2911 (2001)