# Artificial intelligence in purchasing: How to facilitate mechanism design-based negotiations

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## Abstract

Recently, the application of mechanism design theory in negotiations gained enhanced attention. While such negotiations can result in high cost savings, mechanism design-based negotiations require staff with expert knowledge in economics. The research paper aims at answering the question whether artificial intelligence (AI) can facilitate the execution of mechanism design-based negotiations. A group of 20 persons, consisting of purchasing and AI experts from an European automotive OEM, discussed in a World Café the potentials of AI for the purchasing function. The results indicate that the application of AI can indeed facilitate the execution of mechanism design-based negotiations.

**Keywords:** Mechanism design theory, Negotiations, Artificial intelligence

**Introduction**

Many scholars have realized purchasing's eminent impact on the bottom line's performance of large industrial organizations (Schiele et al., 2011; Wynstra, 2016). Especially in times of decreasing depth of value added, suppliers become more important and powerful (Pulles et al., 2014). Hence, advanced negotiation techniques can be seen as a key success factor of purchasing. Still, these negotiations can easily become very complex, as internal targets, for instance on cost, quality, or strategy, need to be met, while achieving an agreement with supply chain partners. In this context, the application of mechanism design theory gained increased interest in the field of purchasing and supply management (PSM) in recent years (Schulze-Horn et al., in press). Mechanism design theory represents the inverse of game theory, i.e. the idea is to design and implement economic incentives to achieve desired objectives (Nisan, 2007). The existing literature indicates that mechanism design-based negotiations represent a promising way to breed competition between suppliers and to achieve cost savings (Drozak Consulting, 2014; Schulze-Horn et al., in press). However, preparing game theoretic negotiation designs requires a lot of expert knowledge in economics. In addition, the cognitive capacity of human individuals is somewhat limited, potentially leading to bounded rational decisions (Simon, 1955). The designing process of such negotiations is very complex as there are several interdependent phases that combine various negotiation elements with diverse incentives such supplier rankings, or information feedbacks. At the same time, it can be observed that research in information technology (IT) makes considerable progress in the domain of artificial intelligence (AI), which aims at developing machines with human-like problem solving skills (Russell & Norvig, 2010). These machines possess a vast amount of computational capabilities, implying the following research question: *Could artificial intelligence facilitate the application of mechanism design-based negotiations?*

## Mechanism design in purchasing

Purchasing is a critical function which allows the firm to increase its profitability (Cox, 1996). To maintain or improve purchasing performance, scholars and practitioners are seeking for new approaches. New or advanced negotiation methods reveal hereby potential to increase the organization's profitability (Metty et al., 2005). In this context, mechanism design theory could be applied to make negotiations more effective (Schulze-Horn et al., in press). Mechanism design theory is the inverse of game theory (Singh & O'Keefe, 2016). The latter analyzes interactions in order to identify optimal outcomes and devise strategies how the games' players can achieve these outcomes (Luce & Raiffa, 1989; Lasaulce & Tembine, 2011). A key assumption in game theory is that interactions are defined by a set of rules which prescribe the players' potential actions and their associated outcomes (Colman, 2008). Mechanism design theory, in contrast, aims at defining the rules of a game in such a way that a desired outcome is achieved (Hehenkamp, 2007).

In the field of PSM, mechanism design-based negotiations recently received growing interest, indicating that those negotiations are likely to result in higher cost savings (Schulze-Horn et al., in press). In general, these negotiations require far more preparation, which makes them quite costly as compared to conventional approaches (Schulze-Horn et al., in press). The underlying rationale of mechanism design-based negotiations is to incentivize suppliers to disclose their last acceptable agreement, i.e. incentives aligned to the negotiation situation are designed to reveal the suppliers' reservation prices. In the study of Roth (2002), mechanism design theory is compared to the subject of engineering because – like an engineer – the mechanism designer is striving to generate mechanisms by exploiting trade as an instrument. Thus, the process of actually designing the specific rules becomes crucial to the success of the entire negotiating situation. However, mechanism design-based negotiations usually include several elements such as auctions, re-quotes, and exclusive offers combined with a variety of incentives that can motivate suppliers to offer price reductions. Therefore, conceptualizing a mechanism design-based negotiation is very complex and requires expert knowledge in this field as well as a higher amount of resources as compared to conventional negotiation approaches.

## Artificial Intelligence

Given the fact that mechanism design-based negotiations are very complex and associated with high levels of expert knowledge, the idea emerged that AI might facilitate this type of purchasing technique. Various scholars have attempted to define AI but the many facets and the scope make it difficult to find a universal definition. However, most researchers agree that AI is a program or computer that simulates the human mind and thus acts intelligently (McCarthy & Hayes, 1981; Haugeland, 1989; Russell & Norvig, 2010). McCarthy et al. (2006, p. 12) even states that "(…) every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it." Already in the 2000s, computers were so intelligent that they won chess games against the reigning world champion. Even though there are ongoing discussions whether winning a chess game is a valid evidence for intelligence (Feng-Hsiung, 1999), it highlights that the capabilities of computers made a considerable step forward in the last decades. In more complex settings such as in the game "Go", this simple logic of a computer chess program is reaching its capacity limits. Search problems will occur that are caused by complex settings, making it difficult for the machine to come to a distinct decision (Korf, 1990). In order to overcome this problem, computer scientists developed heuristic methods, solving the search problem by seeking the optimal dichotomy between completeness and speed. This heuristic approach paved the way for deep reinforcement learning, allowing the defeat of the world's Go champion in 2016 (Pan, 2016). Deep reinforcement learning makes it possible for a computer program to learn how to play a game by only showing the rules of the game. Thereby, the computer program can reach an extraordinary high skill level of playing a specific game (Mnih et al., 2015). From 2010 up to now, research on AI has resulted in additional astonishing successes, such as IBM's AI solution called Watson that won against two champions of the game 'Jeopardy!' in a TV show. Hereby, the program showed its abilities to understand spoken language and answer difficult questions within reasonable time (Ferrucci et al., 2013). Since 2010, technological development has accelerated fast, showing vast potential in the research subject of AI. Based on these recent developments, AI might be the solution of choice to facilitate the regular application of mechanism design theory in negotiations. The purchasers, who would be responsible to conceptualize a mechanism design-based negotiation, have in many cases not sufficient expert knowledge in the field of behavioral economics and game theory. This is not surprising, since purchasers are primarily responsible for a broad set of supply management tasks and not solely focused on the execution of mechanism design-based negotiations. Another issue is the fact that purchasers (and individuals in general) have only restricted capabilities of making rational decisions due to their cognitive abilities (Simon, 1955). The rationality assumption of economics provides thereby a solid foundation for applying a computer scientific approach. This is in line with Nisan (2007) who argues that the interest in realizing game-theoretic concepts with computer scientific facilitation has been a goal since the beginning of the internet.

**Methodology**

As the field of study is relatively new, the research paper has a rather explorative character. For this reason, a qualitative research setting has been chosen. In detail, the World Café method has been applied, which allows taking into account a wider context of information that is provided by the participants (Hüttinger et al., 2014). The underlying rationale of this method is to uncover hidden information through constructive discussions within expert groups (Tan & Brown, 2005). As the purpose of the study is to assess the opportunities to implement AI in buying organizations in order to improve the results of the negotiation process, the World Café method represents a promising way to gain access to the knowledge of the involved individuals. The study at hand was conducted at a large European automotive original equipment manufacturer (OEM) which has several years of experience in conducting mechanism design-based negotiations. Twenty experts who either belonged to the field of PSM or AI were brought together for a World Café session consisting of four tables. All participants were from the case company or in strong relations with the case company (e.g. consultancies). Each table was dealing with a specific question related to the application of AI in purchasing in general as well as in mechanism design-based negotiations in particular. Every participant was asked to join randomly a discussion table and to move on to another table after the round was closed. This procedure was repeated four times. At the beginning of each session, the moderator summarized the results of the previous round, then the groups further elaborated on the already developed ideas. After the four rounds were terminated, all participants were invited to rate the ideas by assigning points in order to identify the most promising insights. After reviewing literature for the two main underlying subjects of the study, i.e. AI as well as mechanism design-based negotiations in the purchasing function, four discussion topics were developed: (1) AI in the purchasing process, (2) AI in mechanism design-based negotiations, (3) implementation of AI in mechanism design-based negotiations, (4) future skills: impact of AI on the purchasing function.

The underlying rationale of topic 1 was to identify general opportunities for the application of AI in the purchasing process, i.e. the discussion at table 1 was not restricted to the actual negotiation part of the purchasing process. Rather it was intended to create an open atmosphere in order to allow the discussants to develop creative ideas of how AI could make the purchasing process more effective and efficient. In contrast, the discussion taking place at table 2 was clearly focused on the question of how AI could specifically support the preparation and execution of mechanism design-based negotiations. Table 3 was concerned with the concrete implementation of AI in mechanism design-based negotiations. Here, the experts were motivated by the moderator to think about the steps that would need to be undertaken as well as the preconditions to apply AI techniques in mechanism design-based negotiations. Finally, table 4 again was a rather broad topic where the participants were invited to share their expectations about the impact of AI on the skill set that purchasers will need in the future.

After collecting the information from the experts during the World Café session, the data has been processed and analyzed. The actual analysis was based on the discussion points that were written down during the session by the moderator of each table as well as the audio recordings of the discussions, which were taken during the discussion rounds. The points on the flipcharts provided the basis of the analysis, the audio recordings were used to verify the discussion points. Overall, the data has been analyzed in a descriptive way rather than in statistical tests.

## Results

During the World Café session, discussions were made at four tables and covered four different topics. In the results section, the main ideas of each table and also the associated expert ratings are presented. As there were a lot of ideas developed, only those ideas for each table are detailed that were responsible for approximately 50% of the cumulated points that were assigned by the experts. By doing so, a focus lies on the most promising results.

*Topic 1 – AI in the purchasing process*

The first discussion table was concerned with the identification of possible AI solutions in the entire purchasing process. The results are presented in the short list which is displayed in Table 1. While the original list included 22 discussion points, the short-list contains four ideas that account for 52% of the points assigned by the experts. For the first discussion table, the following ideas were developed:

(a) ***Cost-optimizing engineering***: AI might help during the engineering stage or the early phase of the purchasing process to identify changes in the product that do not impair the functionality or the quality of the item under consideration but reduce the purchasing costs, e.g. through lower material costs or the avoidance of over-engineering.

(b) ***Analysis of cost-breakdowns***: The cost-breakdowns provided by the suppliers could be evaluated systematically and intelligently to detect hidden cost drivers. Additionally, a database could be created that contains detailed information concerning the cost structure of each supplier.

(c) ***Recognition of price patterns***: AI could identify patterns that reflect the development of commodity or material prices over time. As a result, optimal and anticyclical points of time for the sourcing process could be identified.

(d) ***Analysis of the negotiation behavior:*** AI could be used to analyze the individual negotiation behavior of each supplier to predict how the supplier will behave in the negotiation process.

*Table 1 – Results: AI in the purchasing process (topic 1)*

| **Discussion points** | **Points assigned by AI experts (%)** | **Points assigned by purchasing experts (%)** | **Total points assigned (%)** | **Cumulated total (%)** |
|---|---|---|---|---|
| 1. Cost-optimizing engineering | 20% | 14% | 16% | 16% |
| 2. Analysis of cost break downs | 7% | 18% | 14% | 30% |
| 3. Recognition of price patterns | 4% | 17% | 12% | 42% |
| 4. Analysis of the negotiation behavior | 7% | 13% | 10% | 52% |
| *Rest of discussion points* | *42%* | *20%* | *28%* | *100%* |

*Topic 2 – AI in mechanism design-based negotiations*

The second discussion table aimed at identifying opportunities for AI to support mechanism design-based negotiations. The results of the discussion and the subsequent ratings are presented in Table 2, which is a short list, consisting of those three ideas (out of 13) that gained the most interest, i.e. 58% of the expert ratings.

(a) ***Analysis of the negotiation behavior:*** AI could be used to analyze the individual negotiation behavior of each supplier to predict how the supplier will behave in the negotiation process.

(b) ***Simulation of negotiations:*** AI could analyze the predefined rules of an upcoming negotiation and make predictions on the expected outcomes as well as validity checks of the suggested negotiation design.

(c) ***Development of negotiation designs:*** AI autonomously develops negotiation designs that fit to the individual circumstances of each sourcing project and its market conditions.

*Table 2 – Results: AI in mechanism design-based negotiations (topic 2)*

| **Discussion points** | **Points assigned by AI experts (%)** | **Points assigned by purchasing experts (%)** | **Total points assigned (%)** | **Cumulated total (%)** |
|---|---|---|---|---|
| 1. Negotiation behavior analyst | 27% | 21% | 23% | 23% |
| 2. Negotiation simulator | 15% | 21% | 19% | 42% |
| 3. Negotiation design developer | 18% | 15% | 16% | 58% |
| *Rest of discussion points* | *39%* | *44%* | *42%* | *100%* |

*Topic 3 – Implementation of AI in mechanism design-based negotiations*

The third discussion table was concerned with the actual implementation of AI in the process of conducting a mechanism design-based negotiation. The short list (Table 3) consists of those five ideas (out of 15) that account for 53% of the expert ratings.

(a) ***Simulation of negotiations:*** AI could analyze the predefined rules of an upcoming negotiation and make predictions on the expected outcomes as well as validity checks of the suggested negotiation design.

(b) ***Expert systems:*** Expert systems that aim at imitating human knowledge and behavior could be developed. In the first step, these systems would still require human input and interaction. With an increasing amount of data available, the systems could become more intelligent through machine learning approaches and ultimately make the human input obsolete.

(c) ***Information seeking across systems:*** AI could be capable to collect meaningful data from the various IT systems of large buying organizations and to intelligently merge these data in a way that they facilitate the process of conducting mechanism design-based negotiations.
(d) ***Heuristic mechanism design selection:*** If there are too many and partially conflicting goals and targets of a negotiation, the degrees of freedom might be too high in order to be able to develop one single solution. Heuristic selection systems, supported by AI, might compare the expected outcomes of each proposed negotiation design and then choose the most suitable one. This process could be repeated in various rounds and would result in the survival of the fittest design.
(e) ***Goal definition:*** A precondition for designing negotiation rules is to define goals and premises a priori. So far, the complexity of the goals that can be taken into consideration is somewhat limited by human cognitive capacities. AI could make it possible to include a larger number of goals in the process of designing negotiation rules by providing the amount of cognitive capacity that is needed to do so.

*Table 3 – Results: Implementation of AI in mechanism design-based negotiations (topic 3)*

| **Discussion points** | **Points assigned by AI experts (%)** | **Points assigned by purchasing experts (%)** | **Total points assigned (%)** | **Cumulated total (%)** |
|---|---|---|---|---|
| 1. Negotiation simulations | 15% | 19% | 17% | 17% |
| 2. Expert systems | 8% | 11% | 9% | 26% |
| 3. Information seeking across systems | 3% | 16% | 9% | 36% |
| 4. Heuristic mechanism design selection | 15% | 3% | 9% | 45% |
| 5. Goal definition | 10% | 5% | 8% | 53% |
| *Rest of discussion points* | *50%* | *46%* | *47%* | *100%* |

*Topic 4 – Future skills: the impact of AI on the purchasing function*

The fourth table covered the topic of future skills that are likely to be relevant for the purchasing function as a consequence of the ongoing trend towards AI in business operations. Since the topic of the fourth table was on purpose very open and not directly related to the central research question of this study, expert ratings were not analyzed for the fourth table. Among the discussants, there was a broad consensus that the increasing reliance on AI has two implications. There will be a transformation in the nature of the purchasing function and also the requirements on the purchasing staff will evolve in the future. As a consequence, three fields of action have been identified that should be considered when implementing AI in the purchasing function:
(a) ***Coaching interaction of humans and AI:*** In the future, it might become more important that humans interact with AI. In this case, it will be necessary to train the purchasing staff how (and when) to rely on AI in general.
(b) ***Training in systems:*** If specific applications or systems are developed, the purchasing staff will need training in these specific systems.
(c) ***Building trust in AI:*** As AI is still a rather new theme in business operations, it might create some uncertainties among the purchasing staff how their job profile will be affected in the future and how reliable AI applications are. Accordingly, organizations should dedicate some resources to create trust in this new technology.

## Discussion

In this section, the previously presented results will be discussed in more detail. The topic of the first discussion table was about potential areas of application of AI in the entire purchasing process. The results indicate that the AI experts see the biggest potential in the application of AI already during the development stage of the product life cycle. By doing so, AI could support the engineer also to take cost parameters into account when designing a product. For instance, AI could suggest alternative materials with comparable characteristics that are cheaper than the originally intended ones. The idea of engineering products in a cost-efficient manner is a widely accepted sourcing lever (see e.g. Schiele, 2007; Schiele et al., 2011; Hesping & Schiele, 2016). Schiele et al. (2011) even find in their study that product optimization is expected to result in the highest cost savings of the analyzed sourcing levers. Likewise, also in the domain of engineering it is acknowledged that AI can be used to support the product development process (see e.g. Pham & Pham, 1999; Kwong et al., 2016; Yan Chan et al., 2016). Hence, there seems to be a good match between an idea that can contribute to an improved purchasing performance and the applicability of AI. Another potential application of AI in the purchasing process has been identified as the analysis of cost breakdowns. In many large buying organizations, the suppliers that are interested in being awarded with a sourcing contract are asked to submit a detailed cost breakdown. In these cost breakdowns, the suppliers disclose their entire cost structure which subsequently is verified by a cost expert from the buying organization. The purchasing experts suggest that the data in the cost breakdowns is very valuable for the negotiation process, as main cost drivers can be identified and mitigated (Ellram, 2000). However, in the case company, the information that is contained in the cost breakdowns is not stored and processed in a systematic way, as this would require a vast amount of additional capacities. By means of using AI for the analysis and systematic processing of the data, a powerful tool could be created, entailing supplier specific cost data that could be stored in a supplier folder. Being able to retrieve this data would facilitate the job of the purchaser in various ways, e.g. for the preparation of the negotiation. Similarly, the experts indicated that AI could be used to identify cost patterns, i.e. to make predictions how the costs are likely to evolve over time. From a technical perspective both ideas seem to be feasible (Michalski et al., 2013). The idea to benefit from the systematic storage and analysis of supplier specific data was also mentioned in the context of the identification of individual negotiation patterns. The underlying rationale is that every supplier might have individual traits when it comes to the negotiation process. Previous research demonstrates that it is indeed possible to draw inferences from the supplier's behavior from past transactions (Ray et al., 2011). AI applications could provide the respective cognitive capabilities and resources to make these predictions.

The idea to identify patterns in the behavior of suppliers was also addressed in the second discussion table, which investigated the potential of AI to support mechanism design-based negotiations. In this context, Ray et al. (2011) describe how this behavioral aspect of the supplier can be used in reverse auctions for an efficient supplier selection. Furthermore, at the second discussion table, the idea emerged that AI could be used for simulations of forthcoming negotiations. The experts expressed the belief that a priori it could be tested whether a specific set of predefined negotiation rules actually leads to the intended outcomes. This approach could be connected with the prediction of the supplier specific negotiation behavior and the associated expected outcomes (Carbonneau et al., 2011). Another potential field of application for mechanism design-based negotiations has been identified in the development of the rules for the negotiation. As mentioned earlier in this paper, the actual process of designing the rules of a negotiation in such a way that the intended goals are achieved is a very complex and challenging task requiring high degrees of expert knowledge in game theory as well as increased cognitive capabilities (Schulze-Horn et al., in press). That AI can solve game-theoretic issues and translate them into negotiation designs is in line with scholars such as Jazayeriy et al. (2012).

So far, the discussions at the tables 1 and 2 have indicated that the purchasing function could benefit from the application of AI. At table 3, therefore, the discussion was focused on the feasibility of these ideas, given the current state of the art in AI. Both expert groups agreed that the simulation of negotiations would be a strong enabler for the successful implementation of mechanism design theory in negotiations. From a technical perspective, it seems to be achievable. However, in general the expert groups also agreed that currently the trend leads towards expert systems, still requiring human input and training. By means of machine learning approaches in connection with growing data sets, the degrees of autonomy are indeed likely to rise but these systems will not make the human purchaser obsolete in the near future. The most realistic and achievable scenario would be the implementation of applications that are able to seek information across the borders of single IT systems. It can be argued that in particular large industrial organizations have in principle access to a rich set of highly relevant data. Unfortunately, the data are often spread across different IT systems and various business functions, making it almost impossible for the purchaser to identify all the relevant information. An AI application that can intelligently retrieve and merge information from diverse data sources would be a significant step forward to more effective purchasing processes. Additionally, it was discussed at the third table that even if the current state of the art in AI would not be able to automatically design the negotiation rules for complex sourcing projects, it should at least be realistic and feasible to apply heuristics in order to forecast the outcomes of a given set of negotiation rules. A precondition to do so would be the precise definition of the goals that shall be achieved during the negotiation process.

**Implications for theory and practice**

Starting with the scientific implications, the study somewhat proves that mechanism design-based negotiations are expected to harvest relatively high cost savings, which is in line with Schulze-Horn et al. (in press). Secondly, it has been confirmed by the expert groups that the average purchaser is lacking the expert knowledge in game theory in order to be able to develop rules for a mechanism design-based negotiation by himself. As already suggested by Selten (1991), humans often are exposed to bounded rationality. Due to the limited computational capabilities of their minds, it is unlikely that all decision variables can be taken into consideration. Accordingly, it requires high efforts to come to a rational conclusion, which is often associated with high decision costs (Selten, 1991). However, the results of this research paper point into the direction that AI can surmount the barriers to the application of mechanism design-based negotiations that arise due cognitive constraints of the human nature. Moreover, the experts that were involved in this study also provide support for the research of Jazayeriy et al. (2012) who argue that AI already reached a stage of maturity that is sufficient to conduct autonomous negotiations based on game-theoretic insights. Additionally, it has been found that the application of AI is not limited to the purchasing function itself but also could be applied in adjacent functions, such as research and development (Schiele et al., 2011).

Also from a managerial perspective, diverse implications emerged. At the fourth discussion table it has been debated how the application of AI is likely to affect the purchasing function. The results indicate that the nature of the purchasing function will change in the future towards a more automated state, somewhat reducing the need to carry out purely operative tasks. This implies that the requirements on the purchasing staff will evolve over time. In the long-term, it will be necessary to coach the purchasing staff in the interaction with AI applications. In the near future, it will be essential to train the purchasing staff in the use of expert systems that are indeed partially intelligent but still require human input. Additionally, trust in the new way of working must be created. AI should not be seen as a rival or replacement of the human purchaser. Instead, it should be seen as a facilitator of a more effective and efficient purchasing function.

Interesting directions for future research could be to empirically assess the performance increasing effect of mechanism design-based negotiations. It should also be investigated whether there exist dominant designs or sets of negotiation rules, which could be applied by organizations with limited financial resources.

Nevertheless, it needs to be acknowledged that there are also limitations of the present research setting. The research has been conducted at only one case company from the automotive sector, partially limiting the generalizability of the results. Still, the automotive industry is of large importance for the world economy and often associated with pioneering and innovative approaches, making it a very popular research environment for the field of PSM (Horn et al., 2013; Vos et al., 2016). Another limitation could be seen in the fact that only a group of 20 experts had served as sample for the study. However, the company under consideration has several years of experience in the application of mechanism design-based negotiations. To date there is only a small number of corporations in the automotive sector with this extend of experience.

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