SCUOLA DI INGEGNERIA INDUSTRIALE
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EXECUTIVE SUMMARY OF THE THESIS

The impact of Artificial Intelligence on procurement negotiation: a simulation experiment

TESI MAGISTRALE IN MANAGEMENT ENGINEERING – INGEGNERIA GESTIONALE

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1. Introduction

The phenomenon of digital transformation has become very popular in the recent years (Fitzgerald M. et al., 2013; Kane G. C. et al., 2013). Digital technologies have revolutionized the way industries operate (Dal Mas F. et al., 2020c) and their exploitation offers opportunities to integrate products and services across functional, organizational, and geographic boundaries (Sebastian I. M. et al., 2017). The current digital revolution and the new techno-economic paradigms will challenge companies to redefine and upgrade their systems, acquire new skills, and foster new mindsets (Bojanova I. et al. 2014). Especially due to the Covid-19 pandemic, the firm environment has relied more and more on merging physical and virtual worlds, endowed with an innovative set of technologies. It is a fact the Big Techs companies have enormously increased their capitalization as the demand of their services such as software facilitating remote working, e-commerce and social networks boosted. Despite the global pandemic is having a huge impact on the world economy, there are different other factors that are shaping companies' context, like the dramatic increase in the price of raw materials due to the current war between Russia and Ukraine. In addition, another critical priority of companies' top management is the environmental concern that is asking CEOs to develop always new strategies to reduce the carbon footprint (Gartner, 2020).

Almost all the C-levels of each organization including CPOs (Chief Procurement Officers) are asked to deal with such complex tasks. Particularly, given the high value of Procurement (Bienhaus and Haddud, 2018), organizations should begin conceiving it and its sub-phases (i.e., negotiation, cost management, etc.) as actual strategic activities, with enhanced value-adding processes by employing digital technologies. However, focusing mainly on negotiation, low number of application cases of digital technologies in such realm are present in the current literature. Hence, the main objective of this study is to understand the impact downstream the adoption of AI in the negotiation process, providing practical and concrete support to companies' procurement department.

2. Literature review

The current available literature has been the starting point to broaden the authors' knowledge on three main topics: Artificial Intelligence, Negotiation and Procurement. Particularly, each of them has been addressed narrowing step by step the focus on the topic with the aim to understand potential correlations and links among each other still to be discovered.
Firstly, according to Bienhaus and Haddud (2017), digitisation of the whole procurement process can yield several benefits including supporting daily business and administrative tasks as well as complex decision-making processes. However, following Rejeb, Sűle and Keogh (2018), the technical and economic feasibility of adopting new procurement-enabling technologies is still very challenging and there is yet some uncertainty within companies' culture.
Focusing on negotiation, the dive deep on the topic underlines that it seems to have high potential to be discovered yet, since it is mainly intended by humans like a set of instant messaging tools (Kao, Wang, Kiang, 2020) rather than comprehensive systems to make negotiation more efficient, faster, and less time-consuming.
Overall, the main potential benefits of AI-based negotiation systems include reduced negotiation time and costs and less social confrontation, even if they lack experiments evidence (Lopes et al., 2008). In fact, the broad analysis of the papers related to potential applications of AI in negotiation pointed out two main limits: on one side the absence of applicable and replicable models in real negotiation scenarios due to their high theoretical and too complex nature, on the other the lack of data related to the expected AI tools and AI-generated information on procurement negotiation performances.
Hence, concerning negotiation performances evaluation, the literature proposes generic architectures for the evaluation of such results, mainly based on qualitative metrics (Zetich, 2002). Just one framework was found in literature that provides a structured approach to classify both quantitative and qualitative dimensions according to two types of indicators (ICTPEMOIN Model, Cano J. A. et al., 2014): efficacy (also called effectiveness) and efficiency.

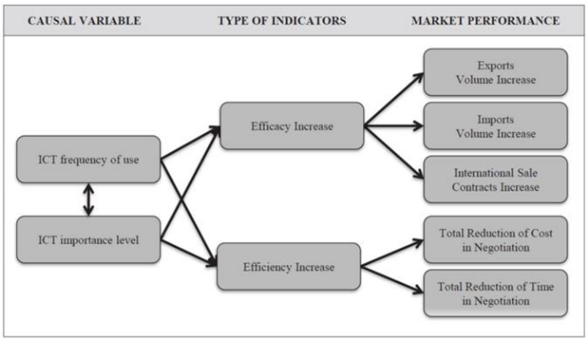

Figure 1: *ICTPEMOIN Model (Cano et Baena, 2014)*

Finally, also barriers to AI adoption have been addressed. Indeed, as it happens for mostly all disruptive technologies adoption, also for AI there are environmental, technological, and social factors influencing such adoption process (Chatterje, et al., 2021), asking companies for a total reshaping of hard and soft skills. This adoption challenges were further confirmed by the TAM (technology acceptance model) framework (Baabdullah, 2021) applied to AI adoption, and reinforce the limits already underlined in the paragraph.

3. Objectives and research process

Objectives
Given the absence of research explaining from a quantitative point of view how AI can affect the negotiation performance in the Procurement department, the aim of this work is to contribute to the state-of-the-art literature and to provide companies effective guidelines for decisions related to AI adoption in procurement negotiation. Hence, to address the objective of enriching the available literature, the authors have formulated two main Research Questions which try to fill the emerged literature gaps.
RQ1: How does the adoption of Artificial Intelligence affect the negotiation performance in the procurement phase of a manufacturing company?
The available literature does not give many insights on these topics; It is stated that Procurement 4.0 phases positively influences both performances and business processes, however it is not investigated which drivers are impacted the most and how. Moretto et al. (2017) explain how AI and Big Data can increase the effectiveness of procurement negotiation decisions, however just

basing the analysis on a qualitative framework, without finding variables able to quantitative evaluate such AI impact.

RQ2: What is the role of the information available to the buyer firm in an AI-based negotiation platform?

The role of information in procurement negotiation is mainly investigated in the current literature considering stand-alone cases. The most common examples consider a buyer-supplier negotiation dealing with asymmetric information and examining opportunities for mutual gain and optimal strategies (Samuelson W. 1984, Schwarz S. et al., 2010). No frameworks were found describing the role of AI generated information in procurement negotiation.

Research process

A methodical and structured multi-step process was followed along this research as described below:

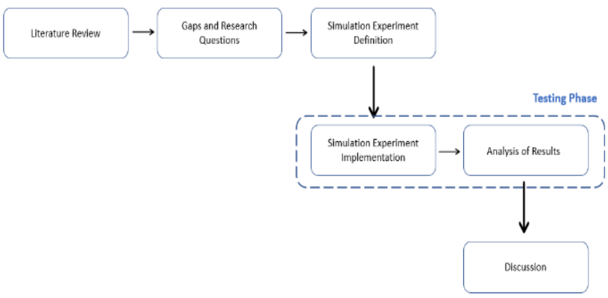

Figure 2: Research Process Schema

The flow starts by introducing a literature review which enables a comprehensive understanding of the state-of-the-art of the AI and its adoption in Negotiation. Exploiting the knowledge accumulated through the literature review, the authors assessed the correlated research gaps and subsequently defined the main goals of their research defining the Research Questions.

Along with formulation of the Research Questions, the authors chose the negotiation experiment with a pool of 24 students as a powerful tool supporting the achievement of the objectives defined, following the models already available in literature. Given the nature of the negotiation process, it is considered appropriate to simulate the negotiation process drafting real-life case studies in the procurement field and submitting them to a class of such graduate students.

The experiment and data collection phase are carried out in one single day with a 2-round negotiation performed. The empirical analysis executed after the data collection has led to different perspectives and conclusions. The authors have opted to investigate the impact of AI in terms of total cost and time savings through single metrics analysis (such as price, delivery time security stock etc.), comparing negotiations supported by AI and "traditional negotiations" without any kind of auxiliary tool.

To sum up, a framework of the overall topics addressed by the Research Questions is presented below to make it easier to visualize the link between RQ1 and RQ2, as well as their positioning along the negotiation stages and components.

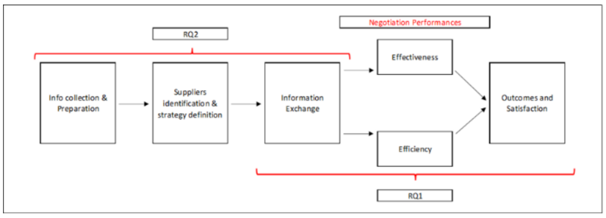

Figure 3: Research Questions Schema

4. Research Methodology

The definition of the whole research methodology was based upon two sources of data: academic and practitioners' literature and case studies.

The starting point was the literature review. Since the two topics of negotiation and procurement are of huge presence in the past decades' publications, as well as artificial intelligence disruption in the last few years papers, such big amount of data needs a robust process for selection, assessment, and dissemination to first answer to the identifies research questions and then to possibly develop future research insights (Ghadge, A., Wurtmann, H. and Seuring, 2019). The literature review process has an explicit search strategy following the identification of 'keywords' or 'search strings'. The structure is composed by 3 main areas (identification of data sources, data extraction and synthesis, data analysis and dissemination), that allowed the authors to reach the final pool of 79 papers considered as necessary to give relevance to the whole work, starting from 329 selected papers.

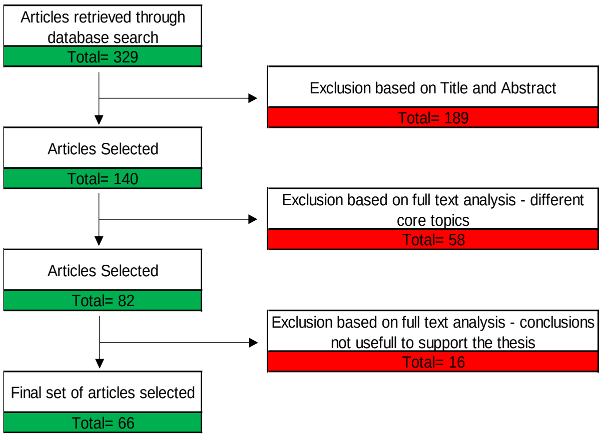

Figure 4: Rivisitation of Annarelli, Battistelli and Nonnino's literature review selection framework (2016)

The "historical distribution" of literature publications was also tracked, with papers ranged from 1995 to 2021.

The authors then moved from the theoretical lenses to the validation on the field, performing an intensive data collection and analysis process employing a negotiation experiment. Such experiment is aimed at evaluating how a set of independent variables is impacted by the power of artificial intelligence in a negotiation case. The focus was twofold: first, there was the need to compare the different results coming from the AI-supported negotiation versus the traditional one to point out the impact of AI on negotiation performances; then, to understand if this approach could be applicable to "test the ground" on expected outcomes before starting an AI implementation. The set of variables listed for the negotiation is reported below.

VARIABLE	DEFINITION
ΔSupply	Is the difference between the max supply guaranteed and the actual consumption (pairs/year). The higher the delta, the lower the risk to go out of stock in case of demand variability
Time of delivery	A cost is associated to each day of delivery waiting. Moltiplication coefficient per country: Italy = 1; Germany = 1,1; China = 2;
Scrap rate	A cost is associated to each 0,01 percentage point of scrap
Security stock	The higher it is, the lower the risk for the buyer to go out of stock in case of demand variability
Payment delay	The higher the payment delay is, the higher flexibility in money
Price	The price cost is computed as the moltiplication between the yearly demand and the Δprice vs current supply

Figure 5: Experiment Variables

The results are then analysed to assess the two research questions defined in chapter 3, adapting the framework designed by Cano & Baena, 2018, already presented in literature, according to two main indicators: efficiency and efficacy.

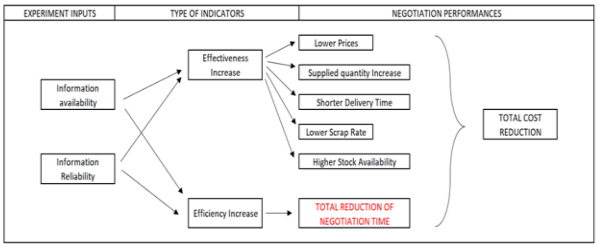

Figure 6: Adapted from the ICTPEMOIN model (Cano & Baena, 2015)

5. Experiment Design

The experiment consisted of four main players: one buyer (RaceCar) and 3 suppliers (Ita-Brake, I-Stop and Nautilus). The cluster of buyers is composed by 3 procurement representatives and each supplier has one sales agent. Moreover, each buyer was assigned to a specific supplier and the couple would perform two rounds of negotiation. On one hand, the buyers were the procurement representatives of an Italian automotive firm that wanted to renegotiate with the current supplier new term for the supply of brake callipers or to enter into an agreement with new international suppliers. On the other hand, the cluster of the suppliers was composed by the sales agents of an Italian incumbent, a German start-up and a multinational Chinese company.

Each player was assigned to a role, a case and, as regards the buyers, an excel file. The cluster of buyers was in turn split in two groups: AI supported, and No AI supported. The buyers supported by AI were provided of market research about the trend of average production cost suppliers sustain to produce brake callipers and the trend of average delivery costs and days of transportation linked with the geographic areas. Furthermore, they were also provided by an intelligent excel file shared among the buyers' group that autonomously calculates the total cost value of the supplier offer.

The structure of the simulation was composed of an introductory part in which the players were given the simulation guidelines and the objectives. Then, two rounds of negotiation of 30 minutes each interspersed by the debrief of the buyers, i.e. the moment in which the buyers could share the information grasped from the suppliers and their impressions. Lastly, once the second round was concluded, the buyers could meet for the final debrief choosing the supplier, while also completing a final feedback survey.

Figure 7: Experiment structure

In conclusion, the authors collected data to later develop the empirical analysis through three main sources: the excel files that contained the value of the variables and total cost, the vocal registration of each round and debrief and a final survey to grasp personal feedbacks on the experiment such as the clearness of tasks submitted, the objectives and the fit of the cases to the reality.

6. Empirical Analysis

The structure of the empirical analysis is presented according to aggregated data, single negotiation variables through a too detailed perspective, a final focus on the overall time spent by players to perform the experiment and a final feedbacks' survey.

Aggregate Data Analysis

The purpose of the aggregated data analysis is to give a comprehensive view of the macro-results of the experiment i.e., the total cost values of each buyer-supplier negotiation.

Generally, every negotiation performed by the students has registered an improvement from the first to the second round, indicating the success of the experiment and confirming that a 2-round negotiation can usually be economically rewarding in a second negotiation (Curhan J.R. et al., 2010).

The data, related to the cluster of buyers supported by AI, presents an average gain compared to the current supply contract (BATNA) of 6%. This result shows that AI based buyers succeeded in beating their BATNA improving the current Ita-Brake offer. Moving towards the cluster of buyers not supported by AI, the same result value considered before is approximately -1%, showing worst performances respect to the AI case with a lack of five percentage points.

Furthermore, as regards the average loss with respect to the optimal value, the results indicate that on average both the AI case and NO AI case have reached worst performances compared to the optimal value. However, it is noticed that group of AI buyers negotiated better deals with the suppliers, beating the expectations of the authors, effectively exploiting the additional information and the smart quantitative framework provided by AI.

Single Variable Data Analysis

	GENERAL	WINNERS
Row Labels	Average of %Δ VALUE	Average of %Δ VALUE
AI	**7,19%**	**-2,99%**
ΔSupply	-11,11%	-66,67%
Payment Delay	5,56%	16,67%
Price	0,23%	-1,25%
Scrap Rate	0,00%	-33,33%
Security Stock	44,44%	0,00%
Time of delivery	4,02%	66,67%
NO AI	**30,25%**	**30,66%**
ΔSupply	66,67%	100,00%
Payment Delay	20,00%	100,00%
Price	1,63%	0,90%
Scrap Rate	-3,33%	-50,00%
Security Stock	30,00%	0,00%
Time of delivery	66,55%	33,04%

Figure 8: Single Variables vs Optimal values (general and winners)

This analysis aims to drill-down the results from the aggregated data analysis and to gain a deeper understanding on each variable negotiated during the experiment.

The first part of this analysis compares the agreed values of each variable versus optimal ones. Data demonstrates that AI-supported buyers have generally performed better respect to the NO-AI buyers in setting and gaining more efficient values of the variables. On average the delta percentage of the loss compared to the optimal value differs of more than 22% between the AI case and the NO-AI case (Figure 8).

Considering solely the data related to the final supplier choice, the improvement of the same variable is even more evident for the AI cluster. Furthermore, four of the six AI impacted variables (66.7%) registered a value that it is better or equal compared to the optimal, due to constraints break

by suppliers not able to properly manage the negotiation.
Conversely, the groups not supported by AI did not improve significantly neither looking at the overall data (also including constraints breaks) nor at the filtered ones.
Comparing the intra-round results, the authors discovered that the intra-round improvement comparing the AI and NO AI cases, is respectively 24,5% and 11,9%. Moreover, the time of delivery variable clearly confirms that having access to additional information increase bargaining power and better results in negotiation. The value of time of delivery has registered a dramatic intra-round improvement of more than 70% (Figure 9).

Row Labels	Average of %Δ ROUND
AI	**24,50%**
ΔSupply	6,11%
Payment Delay	5,56%
Price	2,68%
Scrap Rate	41,67%
Security Stock	19,56%
Time of delivery	71,46%
NO AI	**11,88%**
ΔSupply	17,43%
Payment Delay	-10,00%
Price	2,11%
Scrap Rate	46,67%
Security Stock	-25,64%
Time of delivery	40,71%

Figure 9: Single Variables intra-round improvement

Time Saving Analysis
The scope of this analysis is to investigate and understand whether the AI has an impact in optimizing the time of negotiation.
The authors find a positive correlation between savings in time negotiation and efficient outcomes. Indeed, not only buyers supported by AI manage to improve negotiation performances and reach better deals, but also the total time saved was more than an entire round of negotiation. The students representing the AI buyers successfully succeeded in making and implement decisions faster and more effectively.

Final survey
Generally, the clearness of the experiment and the fit to reality got remarkable score from the players, demonstrating the quality of the preparation and the setting of the experiment. Furthermore, the most significant suggestions to simplify the experiment were to consider separately buyers and suppliers. On one hand, the buyers not supported by AI asked for a real-time information sharing that could have made them aligned to a common strategy and be informed about which variables had higher possibility of improvement. On the other hand, suppliers asked for higher flexibility of constraints and for a framework that could have simplified the multitude of data needed during the negotiation.
Lately, it is emerged that Face-to-face negotiation was largely preferred respect the other alternatives and that the large majority of the respondent was in favour to implement AI in the negotiation to optimize the negotiation process, but with uncertainty for elements considered key in the company's business, on which they prefer human supervision.

7. Results and Discussion

RQ1: How does the adoption of Artificial Intelligence affect the negotiation performance in the procurement phase of a manufacturing company?

Even if it not possible to build an exhaustive model able to show all the possible dimensions affected by AI adoption, the framework designed by the authors and presented in chapter 3 (Redesign of ICTPEMOIN model, Cano & Baena, 2015) gives a structured approach to evaluate negotiation performances. In a three-steps analysis are included all the elements considered essential to answer the question.
The first dimension considered is information as AI plays a crucial role as the biggest, disrupting trend in generating value-added information (Sikendar, 2020), positioning the buyer in an advantage-condition through smoother access and higher reliability of data. However, AI could result even more impactful for what concerns negotiation outcomes. The decision to evaluate the impact from efficiency and efficacy perspective comes from Goncharuk (2017), that suggested this two-dimensions approach to judge performances of a new national healthcare system adoption.
The authors have decided to exploit such dimensions in the evaluation of the AI adoption. The Effectiveness/Efficiency Matrix (created by authors following insights from of Goncharuk et al, 2018 and Cano & Baena, 2015) summarizes the main features representing AI in the experiment

according to their overall impact in the performances:

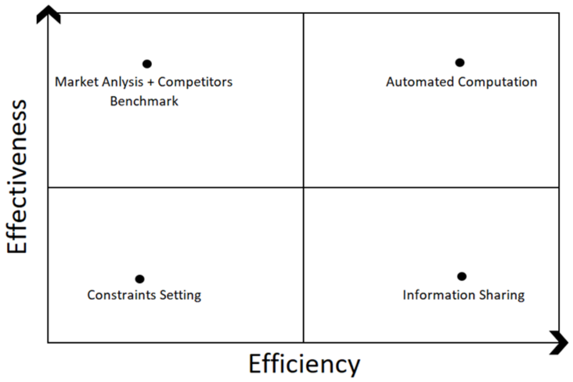

Figure 10: Effectiveness/Efficiency Matrix

RQ2: What is the role of the information available to the buyer firm in an AI-based negotiation platform?
The access to information has a fundamental role in every buyer-supplier negotiation and it influences its outcomes (Fatima S. et al., 2005). Therefore, the authors provide a framework inspired from Cai L. et al., 2015 information dimension architecture, that shows the main characteristics that information available to the buyer firm in an Artificial Intelligence-based negotiation platform must have (as per experiment and final survey confirmation).

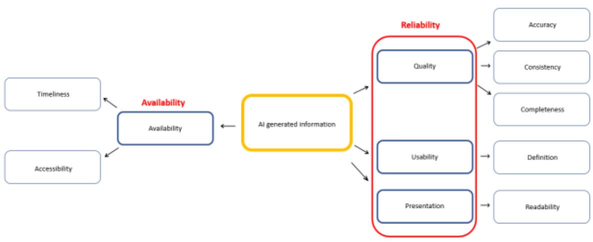

Figure 11: AI Information framework (adapted from Cai L. et al., 2015)

Concerning information availability, intended as timeliness and accessibility of the information, it was investigated during the experiment and through the feedbacks of the players grasped from the final survey. Having access to additional information through the data related to delivery, logistics and production and through the real-time communication among the buyers, considerably makes the groups of AI buyers in advantageous conditions. The results of the experiment regarding the importance of timeliness information in negotiation find confirmations in the research of Campbell T. et al., 2015.

Moreover, moving to information reliability, the experiment showed the importance of accurate computations and structured display of information. The former, ensured by the intelligent excel file, has guaranteed a simplification in defining the total cost values and has helped in agreeing to the final results of the variables. The second, as also stated by Gettinger J. et al. (2012), highlights that the way information is presented influences human decision making (it is especially relevant in e-negotiation) accelerating data analysis and process.

8. Conclusions

Theoretical contributions firstly aim to provide to the current literature a study about the impact of the application of AI in the procurement negotiation process from a quantitative point of view. This work, following Lopes et al., 2018, confirms that the introduction of AI could have a relevant impact on the negotiation performance in terms of cost and time. This dissertation also aims to enrich the scares cluster of publications related to AI applications in procurement negotiation. Moreover, all negotiation models findable in literature tackle the process just from a theoretical standpoint (Zou et al., 2019), lacking practical approaches to replicate for a real negotiation. Lastly, looking at the experiment performed, it can be considered as a pilot project able to give an overview of some relevant metrics (such as time saving or cost reduction per variable) to consider in negotiation that is still missing in papers. Parallelly to theoretical contributions, practical implications have always represented an important dimension to be covered by the authors. Indeed, the other scope of this research is to provide companies some general guidelines that may help them in enriching their understanding of AI potentialities while assessing pain points in their current procurement negotiation process.

Limitations and Future Research

The first limitation is about the reduced number of experimented negotiations performed. In addition, the moment of data collection was too short and just related to the experiment day, obtaining low quantity of information, and therefore conditioning the broadness of the analysis on the topic.

Then, the negotiation process and the experiment design were highly simplified due to the following reasons. First, it was implemented with master students with limited expertise in the negotiation field. Secondly, the authors were given a time constraint of 5 hours to perform all the negotiation rounds. Finally, due to the impossibility to consider all the variables plating a role during any negotiation (i.e., long term relationships, national policies and laws, etc). However, future experiments could involve negotiation professionals, flexing time constraints, considering additional variables and aspects beyond the total cost value, and exploiting real AI tools such as automatization of negotiation computations and chatbots for communication.

To conclude, future developments may be reached by practitioners and academics through new kind of experiments or looking at real market cases. Hence, the exploratory, qualitative nature of negotiation in this study, could find its best realization through the corroboration of results with a real simulation experiment, collecting data on the field with a more quantitative purpose.

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