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Automated Negotiation - Preliminary results of a systematic mapping study

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***Abstract*—Automated negotiation is a process of autonomously overcoming conflicts between intelligent agents and achieving agreement. The literature has proposed several approaches to automated negotiation. To this end, the aim of this study is to summarize the state-of-the-art on automated negotiation for the research community to identify the research gap and to conduct further research in the automated negotiation domain. To achieve this goal, we conducted a systematic mapping study (SMS) on the automated negotiation literature on a set of 73,760 candidate studies. Through a precise search and selection procedure, we identified a set of 21 primary studies, published between the year 2017 and June 2022. As preliminary results of this mapping study, we provide the classification framework to identify and evaluate the automated negotiation literature, and an up-to-date map of the state-of-the-art on automated negotiation focusing on (i) the specific purpose of negotiation, (ii) the application domain in which it is employed, and (iii) how it is carried out in terms of inputs, outputs, and used techniques.**

***Index Terms*—Automated Negotiation, Intelligent Agents, and Automated Decision-making**

I. Introduction

Autonomous artificial intelligence is an evolution of artificial intelligence that enables intelligent agents to act and think like humans and independently perform actions to achieve the desired outcome without human assistance [1], [2]. Such intelligent autonomous agents also interact with each other for collective decision-making [3], [4]. Although these agents can be cooperative and communicate to coordinate decision-making [5], they may also be competitive, leading them to negotiate. Negotiation is a process of resolving conflicts, and automated negotiation is the process where multiple autonomous systems participate in negotiation to resolve differences through dialogues, bids, and offers to reach an agreement that is accepted by all parties involved [6], [7].

Automated negotiation has attracted the interest of the research community in recent years, as intelligent agents that negotiate on behalf of humans are likely to be more efficient [8]. The literature has proposed several studies in this direction; however, until now, despite growing interest, the literature has not provided a comprehensive review that emphasizes (i) the main goal of negotiation and (ii) the studies that provide practical implementation of the proposed approaches to automate the negotiation process. Additionally, in the literature, the negotiation application domain has also not been explored, i.e., it is unclear in which fields negotiation among autonomous agents is applied. This detail is necessary to expand the studies applied in one domain to other domains. To this end, following the guidelines proposed in [9] and the principles in [10], [11], we conducted a systematic mapping study of the automated negotiation literature on a set of 73,760 studies published between the year 2017 and June 2022. We then extracted 21 relevant primary studies from this set through a rigorous search and selection process (further detailed in Section III-B). In this paper, we present some preliminary results of our systematic mapping study, concerning: (i) the specific purpose of negotiation, (ii) the application domain of these studies, and (iii) how the negotiation is carried out in terms of inputs, outputs and used techniques.

The remainder of the paper is structured as follows. Section II provides related work from the state-of-the-art. Section III describes the design used to conduct the systematic mapping study. Section IV illustrates the preliminary results of the mapping study. Section V provides a discussion of research challenges. Section VI details the threats to the validity of the study and Section VII closes the paper.

II. Related Work

In this section, we provide related work on the state-of-the-art of automated negotiation.

The study in [12] provides an overview of the life cycle of negotiating agents and the techniques they can use at different stages of their life cycle. The study also details how agent preferences play an important role in agreement or disagreement, as agents accept and reject offers based on their private preferences. Unlike this study, our work relies on a systematic process to identify the relevant literature in this field and provides a more complete overview of the techniques used.

A recent survey in [13] focuses on strategic approaches that help the negotiating agent to generate effective offers during negotiation. This study explores different economic decision support mechanisms during negotiation that help the composition of offers at different stages of negotiation to improve the likelihood of achieving the desired outcomes. On the contrary, our research does not concentrate solely on offer generation. Instead, we explore a broader range of studies that propose techniques to automate the entire negotiation process. In addition, another recent study published in [14] provides

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a systematic review of decision-making system based on distributed multiple agents. These systems employ a conflict resolution strategy to overcome those cases in which discording answers are given by the different agents that compose the system. The authors report that, among the possible conflict resolution strategies, negotiation is the most adopted. However, adopted negotiation techniques and their characteristics are not reported.

In addition, the study in [15] provides a survey of techniques that can be used for opponent modeling during negotiation, and methods to choose the right bidding strategy using machine learning are given in [16]. Furthermore, the study in [17] provides a review of the machine learning techniques used for negotiation in different domains. Comparatively, our scope is broader, as we extract studies that propose approaches for negotiation in different domains and for different stages of the life cycle, which possibly rely on negotiation techniques not only based on machine learning. Furthermore, the mentioned works consider studies that theoretically discuss decision-making. Instead, in our mapping study, we only include studies that provide a practical evaluation of the proposed approach for the automation of the negotiation process.

III. Study Design

To conduct the systematic mapping study, we followed well-known guidelines proposed in [9] and the principles proposed in [10], [11] to formulate our study into three main phases, i.e., planning, conducting, and documenting.

Planning – At this stage, we focused on (i) the need to conduct such a mapping study (arising from the gaps in related work previously discussed) and (ii) defining our research questions (Section III-A).

Conducting – During this stage, we followed the required steps to conduct the mapping study, such as (i) searching and selecting relevant studies (Section III-B) and (ii) scrutinizing each study to extract relevant data following our classification framework, as shown in Table II.

Documenting – During the final stage, we concluded the process with (i) an in-depth elaboration of the data extracted in the previous phase, with the main goal of setting the obtained results in their context (Section IV), (ii) a detailed discussion of possible threats to validity (Section VI) and (iii) writing the final document (i.e., the systematic mapping study).

A. Goal and Research Questions

Goal – The aim of this study is to help the research community summarize the state of the art on automated negotiation, while highlighting existing limitations, open challenges, and future research directions. Specifically, the goal of our mapping study is formulated using the goals-question-metric perspectives (i.e., purpose, issue, object, viewpoint [18]). Table I shows the resulting outcome.

To achieve this goal, we have formulated the following research questions.

RQ1: What is the specific purpose of negotiation?

TABLE I
Goal of this research

Purpose	Identifying and accessing
Issue	the techniques and approaches used for automated negotiation
Object	in state of the art for automated decision making
View Point	from a researcher's and practitioner's point of view

This research question helps in categorizing the negotiation literature by identifying the issues that can be solved through negotiation and the application domains in which it can be applied.

RQ2: How is the negotiation process carried out?

This research question investigates which techniques are used, the inputs required, and the outputs obtained by the negotiating agents proposed in the literature.

B. Search and Selection Process

In the following, we detail the search and selection process we applied to include or exclude any potential study for this research.

Manual keyword search – To apply the search and selection procedure, we first selected top-level venues for software engineering and artificial intelligence research. For conferences, we adopted the *GII-GRIN-SCIE-Conference-Rating*[1] as a reference list to select all conferences ranked A or higher in the domains of interest. This conference ranking is maintained by a group of Italian and Spanish Professors in the domain of *computer engineering and computer science*. For journals, we used the *SCOPUS* database[2] as a reference and selected all potentially relevant journals by searching the top 10% journals in the subject areas of interest for our research (i.e., *computer science, artificial intelligence, software engineering, computer science applications, and general computer science)*. This selection of top-level venues has led to 24 conferences and 22 journals. The full list of selected venues is available online in the replication package[3].

We then performed a keyword search, using as keywords the words *negot* and *agree* within these venues. These keywords were chosen because they represent the root form of the words that are often found in research titles in the field of automated negotiation (i.e., *negot* for negotiate and negotiation, *agree* for agreement). Rather than using key-words in conjunction, each keyword was used independently. This yielded a comprehensive range of results without limiting the search to only conjunctions. This step was carried out within the Computer Science Bibliography from the University of Trier (i.e., DBLP [19]), considering a time frame that goes from January 1, 2017 to June 30, 2022. This search resulted in a total of 73,760 studies, of which 56,819 were the results of conference proceedings and 16,941 belong to journal

[1] https://scie.lcc.uma.es:8443/
[2] https://www.scopus.com/sources
[3] https://github.com/mashalafzal/Automated-Negotiation-SystematicMappingStudy

publications. Subsequently, selected keywords were found in a total of 140 potentially relevant studies, with 118 studies selected by searching in conference proceedings and 22 studies selected by searching journal issues.

Apply selection criteria – The resulting studies were further filtered according to the inclusion and exclusion criteria discussed below. We followed the guidelines from [20], [21], to carry out the selection process in a time efficient and objective manner. Studies that did not meet the inclusion and exclusion criteria were excluded, making up a total of 22 primary studies. This reduced number of results is expected, as the selected venues are broad and cover diverse areas of computer science and artificial intelligence.

To minimize the possibility of biases, we followed well-known guidelines to conduct systematic literature reviews from [10] and defined *inclusion* and *exclusion criteria* prior to performing the selection of relevant studies. In the following, we detail the set of inclusion and exclusion criteria that guided the selection. Note that any study that satisfied *all* inclusion criteria was included. However, any of the studies that satisfied *at least one* of the exclusion criteria was discarded. The inclusion and exclusion criteria are listed below.

Inclusion Criteria

- I1 Studies in which autonomous systems take decisions as a result of agreements reached through negotiation processes.
- I2 Studies proposing methods to automate the negotiation process (e.g., through machine learning and negotiation protocols).

Exclusion Criteria

- E1 Studies that consider only human-to-human interaction without involving any autonomous system.
- E2 Secondary studies, such as surveys and literature reviews.
- E3 Studies lacking a technical description of the proposed method.

Data extraction – During this stage: (i) the classification framework was designed for the data extraction activity, (ii) the primary studies selected during the previous steps were further investigated to extract meaningful data, and (iii) duplicate studies were merged.

Our classification framework is divided into two distinct parts, one for each research question of our study. The overview of the classification framework and the respective parameters are reported in Table II, while the results for each specific parameter are given in Section IV.

Later, the duplicate studies present in the set of selected studies were merged, i.e., papers that were found to be the same but published in multiple venues. In our case, studies [22] and [23] both focus on agreement for cooperation using Monte Carlo tree search. These studies were merged as PS21(a) [22] and PS21(b) [23] since both studies propose the same technique, published by the same authors in different venues. The merged studies are counted as one throughout the article, resulting in a total of 21 studies. The final list of selected primary studies is available online in the replication package[4].

TABLE II
OVERVIEW OF THE CLASSIFICATION FRAMEWORK

RQ	Goal	Parameters
RQ1	Specific Purpose	Negotiation purpose Application domain
RQ2	Techniques, Input and Output	Negotiation inputs Negotiation outputs Techniques used for automation

IV. RESULTS

This section provides a detailed explanation of each parameter involved in the classification framework and illustrates the related data extracted from primary studies.

A. Specific Purpose (RQ1)

In this section, we present the results for parameters related to the purpose for which negotiation is employed.

Negotiation purpose – The purpose of the negotiation represents the main goal for which the negotiation techniques were employed. Through careful analysis of primary studies, four main purpose categories emerged from the keywording process: *reward maximization*, *opponent modeling*, *preference elicitation*, and *agreement for cooperation*. Table III summarizes the primary studies divided by their goal and, in the following, we discuss each of the four goals in detail. Some studies focus on more than one goal, and so are counted more than once in Table III.

TABLE III
STUDIES GROUPED BY PURPOSE

Purpose	Studies #	Primary studies
Reward maximization	18	PS1, PS2, PS3, PS4, PS5, PS6, PS8, PS9, PS10, PS11, PS12, PS13, PS14, PS15, PS16, PS18, PS19, PS20
Opponent modeling	8	PS1, PS2, PS4, PS5, PS8, PS10, PS12, PS17
Preference elicitation	4	PS13, PS16, PS18, PS20
Agreement for cooperation	3	PS3, PS7, PS21

Reward maximization – The majority of the primary studies (18/21) propose techniques to maximize rewards. In particular, most of the proposed studies focus on negotiation for a price, leveraging a utility function to maximize the reward for the agents, depending on opponent offers.

Example: The primary study PS8 [24] proposes a generic agent model in which the agent tries to increase its own reward during the negotiation. The agent takes into account

[4]https://github.com/mashalafzal/Automated-Negotiation-SystematicMappingStudy

the negotiation time and learns from opponent offers using reinforcement learning to update its bidding and acceptance strategies to maximize its own utility over other agents.

Opponent modeling – Knowing the strategies of the opponents is important for an agent to improve its negotiation strategies [25]. Opponent modeling is a process in which the agent predicts the actions of the opposing party to improve its own decision-making process. A total of 8 studies in our selected primary studies focus on opponent modeling.

Example: The primary study PS17 [26] focuses on modeling opponent preferences to improve its own performance. The agent learns and continuously updates its own strategies in a bilateral negotiation with incomplete information about its opponent to update its bidding strategies and increase the chance of winning the negotiation in terms of more reward.

Preference elicitation – Designing agents that can effectively acquire and integrate user preferences into decision-making during negotiation is an open research direction [27]. For this goal, we grouped the studies that propose novel preference elicitation methods to better capture the users' preferences, both autonomously and assisted. A total of 4 primary studies fall under this goal.

Example: PS20 [28] introduces a novel agent-based approach to negotiate the permission to access private data between users and online services. The agent proposed by the authors autonomously negotiates potential agreements for the user, which they can refine by manually continuing the negotiation. The agent learns from these interactions and updates the user model in subsequent interactions.

Agreement for cooperation – While in most negotiation approaches, agents focus on maximizing the reward for themselves, some of these studies propose approaches in which agents perform a task cooperatively. We group the latter studies with this goal. In total, 3 primary studies fall into this category.

Example: The study PS3 [29] introduces an approach called distributed emergent agreement learning (DEAL). It enables agents to suggest agreements to other agents to complete a task more efficiently. The approach has been evaluated in the context of a smart factory, where agents perform a task with cooperation through bilateral agreement and divide the reward in exchange for services provided.

Application domain – This parameter is focused on the application areas of the negotiation approaches. Table IV provides a list of application domains extracted from the selected primary studies. A total of 8 studies focus on negotiation techniques where agents negotiate price; thus, these studies are merged in *economics* group. Similarly, a total of 8 studies instead generate offers without considering a specific domain. Therefore, these techniques have been grouped under *unspecified* domain. A total of three studies focus on a *cooperative environment* where agents negotiate in order to perform a task cooperatively and share the reward. Finally, a single study focused on *competitive environment* in which agents consider each other as opposing players, and also another single study focused on the *privacy* domain, in which the object of negotiation is to grant permissions to social network applications on behalf of the human user.

TABLE IV
STUDIES GROUPED BY APPLICATION DOMAIN

Domain	Studies #	Primary studies
Economics	8	PS1, PS2, PS9, PS11, PS15, PS16, PS18, PS19
Unspecified	8	PS4, PS6, PS8, PS10, PS12, PS13, PS14, PS17
Cooperative environment	3	PS3, PS7, PS21
Competing environment	1	PS5
Privacy	1	PS20

B. Techniques, Input and Output (RQ2)

In the following, we present the results for parameters related to the technical details of the approaches used in primary studies.

Negotiation inputs – This parameter is used to summarize the inputs used by the techniques proposed in the primary studies, as given in Table V. A total of 9 studies take as input *reserved, preferred, and initial price values* to negotiate the price of products or services. A total of 8 studies utilize *opponents' offers history* as input. Consequently, 4 studies take as input the history of offers of the user and 3 studies require as input previous *arguments and dialogues* from which information is inferred.

Example – In PS1 [30], the agents negotiate to buy or sell a laptop. The lowest price to buy a laptop and the highest price to sell it are fixed as reserved values before the negotiation begins. The agents negotiate by exchanging price offers starting from an initial price value, e.g., *"I want to buy it for 50 points"*. If the buyer agent bids higher than the seller agent's reserve value, the deal will be automatically accepted.

TABLE V
STUDIES GROUPED BY INPUT

Inputs	Studies #	Primary studies
Reserved, preferred and initial price values	9	PS1, PS6, PS7, PS9, PS14, PS15, PS18, PS19, PS21
Opponents' offers history	8	PS1, PS2, PS4, PS5, PS8, PS10, PS12, PS17
User's offers history	4	PS13, PS16, PS18, PS20
Arguments and dialogues	3	PS3, PS9, PS11

Negotiation outputs – This parameter is used to describe the outputs of the negotiation process. In Table VI, we present the outputs of all primary studies in two groups. A total of 14 studies provide as negotiation output *counter-offers* by specifically analyzing the opponent offers, while a total of 7 studies provide as output the *final accepted offer* and *the reward* associated with that offer.

Techniques used for automation – This parameter provides the list of techniques used by our selected primary studies to automate the negotiation process as given in Table VII. The

TABLE VI
STUDIES GROUPED BY OUTPUT

Outputs	Studies #	Primary studies
Counter offers by analyzing opponent offers	14	PS1, PS3, PS6, PS7, PS9, PS11, PS13, PS14, PS15, PS16, PS18, PS19, PS20, PS21
Final offers, rewards for agreement and cooperation	7	PS2, PS4, PS5, PS8, PS10, PS12, PS17

total number of techniques mentioned in the table is less than the total number of primary studies, as some studies employ the same technique. However, some studies also employ more than one technique.

Example – In PS1 [30], two opponent agents follow the alternative offer protocol to generate offers one by one for automated negotiation. The agent also uses deep reinforcement learning to learn the opponent's strategies to generate offers.

TABLE VII
PRIMARY STUDIES BY USED TECHNIQUE

Technique	Studies #	Primary Studies
Reinforcement Learning (Q-Learning and DRL)	7	PS1, PS2, PS3, PS4, PS7, PS8, PS12
Alternative Offer Protocol	6	PS1, PS4, PS8, PS14, PS17, PS20
Gaussian Probability	4	PS5, PS10, PS13, PS16
Monte Carlo Tree Search	2	PS10, PS21
Argumentation Framework	2	PS9, PS11
Competitive Negotiation Protocol	1	PS2
Linear Regression	1	PS6
Bayesian Learning	1	PS10
Markov Decision Process	1	PS13
Linear Programming	1	PS15
Multi bipartite gradient descent search	1	PS17
Fuzzy Systems	1	PS18
Equilibrium Strategies	1	PS19

V. Discussion

In this section, we discuss the challenges observed from the preliminary results of this study.

Is it possible for an agent to negotiate on behalf of a human knowing her preferences? An interesting fact observed in the literature (as given in Table III) is that only 4 studies consider user preferences in negotiation. Additionally, as given in Table IV only one study focuses on privacy, where the agent fully negotiates on behalf of the human to grant permission to access her private data to an online service. Representing user preferences and specifically representing user's ethical preferences in negotiation would be an essential step towards developing such intelligent agents that represent humans for decision-making without their intervention. Additionally, this also plays an important role towards the emerging field of trustworthy AI [31], [32].

Is it possible to have a general-purpose automated negotiating agent? As presented in Table IV, the majority of the studies propose techniques that focus on negotiation for domain-specific applications; This highlights an existing research challenge, identifiable in the need for a general-purpose negotiating agent that can generalize its behavior and adapt to multiple environments and resource types.

VI. Threats to Validity

In this section, we discuss the threats to validity in the context of our research and how we mitigate them.

External validity – This stage deals with the validation of the quality assurance risk [11], by evaluating whether or not the proposed study surmises the state-of-the-art literature. To deal with this type of risk, only top-level venues were selected, followed by a manual keyword-based search and selection process. We then applied the inclusion and exclusion criteria, which led to further refinement of the proposed study.

Internal validity – At this stage, we focused on validating the risk of the study design [11]. The research protocol and the classification framework were designed to deal with this type of risk. We rigorously followed the classification framework detailed in Section III to present a methodological point of view of our study.

Construct validity – This stage deals with validating the justification and compatibility of the primary studies with the research questions [11]. To reduce this type of risk, the studies were manually extracted from only top-level venues in computer science and applications.

Conclusion validity – This stage is focused on ensuring the validity of the conclusion derived based on primary studies [11]. The research protocol was strictly followed for data extraction, which helped ensure that the collected data are useful to answer the research questions. The guidelines from [10], [20] were followed to mitigate this type of risk and to ensure transparency in our research.

VII. Conclusion

In this paper, we provide the preliminary results of the Systematic Mapping Study (SMS), focusing on the state-of-the-art on automated negotiation to identify the specific purpose and application domain of negotiation and to extract inputs, outputs, and techniques used to automate the negotiation process. For this reason, we selected 21 primary studies from a total of 73,760 relevant studies through a detailed search and selection process. We applied keyword-based search to extract relevant studies from 24 conference proceedings and 22 journal issues published between January 2017 and June 2022. We then applied inclusion and exclusion criteria to further extract potentially relevant studies.

We presented a classification framework used to achieve the above-mentioned goal and preliminary results of our systematic mapping study. This mapping study can be a resource for the research community, helping to find potential studies published in the domain of automated negotiation that also consider practical implementation aspects.

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