A Systematic Mapping Study on Automated Negotiation for Autonomous Intelligent Agents

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Information Sheet

1. **What is the novelty and significance of the research area being surveyed in the context of autonomous agents and multiagent systems?**

   Automated negotiation is a compelling research field that concerns interaction among multiple agents. In general, negotiation is a process between multiple agents in which a decision is made jointly by communication, i.e., through the exchange of dialogues, bids, and offers to reach an agreement that is further accepted by all agents in a multiagent environment.

   Main contributions are:

   - A classification framework for identifying and evaluating techniques and approaches for automated negotiation in the literature according to several parameters (e.g., focus of the paper, inputs, and outputs of the negotiation process, techniques applied and type of agents involved in the negotiation);
   - an up-to-date map of the state-of-the-art proposed in the domain of automated negotiation;
   - a list of techniques used for automating the decision-making process involving autonomous agents in a negotiation process;
   - a discussion about promising challenges and their consequences for future research on automated negotiation;
   - a replication package for duplication and verification of our proposed study.

2. **Explain how you have sought to ensure that your survey is not merely an arbitrary summary of different pieces of work in this area, but is in fact a rigorous and methodical analysis of the area.**

   We performed a systematic mapping study (SMS) starting from 73,760 potentially relevant studies. Through a precise selection procedure, we identified 53 primary studies, published from the year 2000 onward, which were analyzed by applying a rigorous classification framework.

   For conducting this systematic mapping study, we structured our research into three main phases, commonly employed in systematic literature studies: planning, conducting, and documenting.

   1 **Planning:** We focused on (i) the need to conduct such a mapping study (arising from the gap in the state-of-the-art) and (ii) defined our research questions.

   2 **Conducting:** We followed the required steps to conduct the mapping study, such as (i) searching and selecting relevant studies, and (ii) scrutinizing each study to extract relevant data following our classification framework.

   3 **Documenting:** 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, (ii) a detailed discussion of possible threats to validity, and (iii) writing the final document (i.e., the systematic mapping study).

3. **Have survey papers on the same research area been published and, in particular, have any been published recently? If so, list them.**

To the best of our knowledge, recently, there are no other survey papers that specifically focus on the latest automated negotiation approaches for autonomous intelligent agents. However, in the paper, we compare with (i) a 2004 literature review focused on bilateral negotiation approaches, only those formulated as game theory problem, and (ii) a 2001 survey focused on approaches for negotiation in multi-agent environments, for self-interested agents only.

4. **What are the main differences between your survey and these previously published papers?**

   As already said in previous question, apart from a couple of dated papers in 2001 and 2004, recently, there are no other survey papers that specifically focus on the latest automated negotiation approaches for autonomous intelligent agents.

   Despite the growing interest on automated negotiation, the literature does not provide an up-to-date comprehensive review that emphasizes (i) the main goal of negotiation and (ii) the approaches having a practical implementation that automate the negotiation process.

   Our paper covers studies published from 2000 onward.

5. **Have you published parts of your paper before? If so, give details of the previous paper(s) and a precise statement detailing how your paper provides a significant contribution beyond the previous paper(s).**

   We published a short paper as a very preliminary version of the systematic mapping study. In this paper we thoroughly extend the short paper by also performing backward and forward snowballing to evaluate the studies that are cited by the set of our selected relevant studies and the studies that have cited the set of our selected potential studies. This led to the identification of many more studies published from 2000 onward not included in the previous preliminary version (covering only the years from 2017 to 2022). Moreover, the current study also discusses the limitations of the current approaches, open issues, future challenges, and research trends in automated negotiation, not discussed in the previous short paper.

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Abstract

Autonomous intelligent agents are known as artificial intelligence software entities that can act on their own and can take decisions without any human intervention. The communication between such systems to reach an agreement for problem-solving is known as automated negotiation. This study aims to systematically identify and analyze the literature on automated negotiation. For this purpose, we performed a systematic mapping study (SMS) starting from 73,760 potentially relevant studies. Through a precise selection procedure, we identified 53 primary studies, published from the year 2000 onward, which were analyzed by applying a rigorous classification framework. As a result, we provide an up-to-date map of the state-of-the-art research in the automated negotiation domain. We also provide a replication package to help researchers replicate and verify our systematic mapping study. The results and findings will benefit researchers and practitioners to identify the research gap and conduct further research to bring dedicated solutions for automated negotiation.

Keywords: Autonomous intelligent agents, Multi-agent systems, Automated negotiation, Automated decision-making

1 Introduction

The rapid evolution of artificial intelligence (AI) has given rise to autonomous intelligent agents that can perform actions without human intervention, such as driver-less cars and drones. The exponential growth in information technology has led to the use of AI in everyday life [19, 49]. From autonomous vehicles to intelligent agents that can communicate on the behalf of users in e-Commerce, technology is dominating everywhere [14, 80, 98]. Autonomous artificial intelligence is the evolution of artificial intelligence, where an autonomous system performs various actions to generate an anticipated outcome, without requiring any human support, which helps in the development of intelligent autonomous systems [83]. Such intelligent autonomous systems can have two types: cooperative and competitive. Cooperative autonomous systems communicate with each other to perform a shared task [25, 77]; whereas competitive autonomous systems are selfish and only interact to maximize their own utility [38, 85]. Therefore, how these systems interact with each other and autonomously resolve conflicts or, more generally, agree on matters of mutual interest is the focus of interest. One of the possibilities to resolve conflicts between autonomous systems is negotiation between these systems, which has gathered the research community's interest in automated negotiation.

In general, negotiation is a process between multiple agents in which a decision is made jointly by communication, i.e., through the exchange of dialogues, bids, and offers to reach an agreement that is further accepted by all agents [16, 99]. In the context of automated negotiation, designing agents capable of effectively acquiring and integrating users' preferences into decision-making processes is a key challenge [25, 55]. Automated negotiation is a compelling field of research that groups three familiar research fields into one, namely, game theory, economics, and artificial intelligence [9]. The significance of automated negotiation is receiving great attention in the present age, as intelligent agents who negotiate with each other and represent human users are likely to be more efficient [3].

To meet the growing demand for automated systems involving intelligent agents, the literature reports several works on automated negotiation. Until now, despite growing interest, the literature has not provided a comprehensive review that emphasizes the main goal of negotiation and provides studies that present practical implementation of approaches to automate the negotiation process. In addition, the literature does not cover the application domain of automated negotiation studies, which is needed to expand these studies to other domains. As a step forward, we present the systematic mapping study of the automated negotiation literature, dividing our goal into research questions as mentioned in Section 4.1, which presents a systematic analysis of the automated negotiation literature to cover the shortcomings of the literature by selecting potential studies through a set of parameters.

The goal of this systematic mapping study is to differentiate existing research in the field of automated negotiation from four distinct viewpoints: (i) identifying the specific purpose of the studies published in the domain of automated negotiation, (ii) extracting the input, outcome, and techniques used to model the negotiation process, (iii) finding the limitation of the state of the art and extracting the future research directions, and (iv) analyzing research trends in automated negotiation.

To attain this goal, the methodology for systematic mapping study from [73, 88] is applied, which concentrates on answering the research questions about the state of the art by proposing a reproducible, objective, and unbiased approach. For the proposed systematic mapping study, we applied a rigorous search and selection procedure starting from an initial set of 73,760 potentially relevant studies belonging to 24 conference proceedings and 22 journal issues, leading to the identification of 53 primary studies on automated negotiation, which were then analyzed by applying a pre-defined classification framework. In the end, a translucent picture of the state of the art for automated negotiation is obtained by synthesizing the acquired data.

The major contributions of our study are:

1. A classification framework for identifying and evaluating techniques and approaches for automated negotiation in the literature according to several parameters (e.g., focus of the paper, inputs and outputs of the negotiation process, techniques applied, and type of agents involved in the negotiation);
2. an up-to-date map of the state of the art proposed in the domain of automated negotiation;
3. a list of techniques used for automating the decision-making process involving autonomous agents in a negotiation process;
4. a discussion about promising challenges and their consequences for future research on automated negotiation;
5. a replication package for duplication and verification of our proposed study.

The rest of the paper is organized as follows. Section 2 provides background knowledge of the negotiation process. Section 3 lays out our study with related work. Section 4 presents the design of our study from a methodological point of view. The results of our study are presented in Sections 5 and 6. Section 7 discusses future research challenges and threats to validity are discussed in Section 8. Section 9 concludes the mapping study.

2 Background

In this section, we introduce preliminary concepts, such as the definition of the automated negotiation process and the life cycle of involved agents.

Negotiation is the process of exchanging bids and offers through communication to reach an agreement on a conflicting issue [16, 99]. The negotiated agreement is reached through communication between all agents involved in negotiation having shared and opposite interests. It is also possible that the agents do not agree on offers and the negotiation ends in disagreement. Besides offers, the time allocated for negotiation and agents' preferences are important factors for disagreement [51, 76]. In the case of *automated negotiation*, autonomous agents act on behalf of individuals to reach an agreement through iterative rounds of offers [64]. The agents are designed to function without any human intervention [32], while representing users' preferences and understanding opponent strategies, as to gain more rewards during the negotiation process.

The life cycle of an autonomous negotiating agent is shown in Figure 1. It is divided into three phases [18, 51], namely, *pre-negotiation*, *negotiation*, and *post-negotiation*.

Fig. 1 Life cycle of the negotiating agent

The first step before starting the negotiation process between agents is pre-negotiation. During pre-negotiation, the agents are focused on finalizing the attributes and private preferences of each agent, before initiating the negotiation. For instance, in a negotiation scenario in which a buyer agent and a seller agent interact to carry out a purchase, the seller agent sets a value for the preferred price that it would like to achieve and a second value for the minimum reserved price below which it cannot accept any offer. Similarly, the buyer agent sets values for the preferred price and for the maximum reserved price. To make a deal during the negotiation, the final offer shall lie between preferred and reserved values. Moreover, the time duration for finalizing an offer or terminating the negotiation process on no-deal conditions can also be defined during the pre-negotiation phase.

The negotiation stage comprises offer generation, opponent modeling, offer evaluation, and an acceptance model for decision-making [51]. The negotiating agents follow a negotiation protocol which is defined as the set of rules to carry on the negotiation process. An example of one of these protocols is the multi-lateral negotiation protocol, in which participating agents take a decision cooperatively by agreeing mutually on a decision [21]. Other examples are the one-shot protocol in which one agent makes an offer that the opponent agent can either accept or reject [46], and the alternative offer protocol where every agent can make an offer alternatively [7]. The agents follow one of the negotiation protocols to interact with opponent agents. Moreover, the literature provides different techniques to automate the negotiation process, e.g., in [17], the agents use Q-learning to learn a bidding strategy until the agreement between agents is reached. A review of some of the techniques for automating the e-negotiation process is mentioned in [41]. However, the study does not cover the state of the art. In Section 5.2, we provide a list of techniques mentioned in the state of the art for automated negotiation.

Before the last stage, which is referred to as post-negotiation, the agreement or the disagreement on offers is already decided. Hence, post-negotiation is optional. If the agents involved in the negotiation have found an agreement, its effectiveness can be evaluated during this phase. The effectiveness is evaluated in terms of agent utility or reward. Ideally, in the reached agreement the reward is higher for both agents involved in the negotiation rather than for only one agent [51]. For instance, in the same scenario mentioned above where the agents interact to carry out a purchase by declaring preferred and reserved prices. The effectiveness of the decision can be evaluated by comparing the final offered value with the preferred value of both agents.

If the final offered value is near the preferred value of both agents, it can be referred an effective decision [16].

We further discuss the examples and techniques used for automating the negotiation process below in Section 5.

3 Related work

In this section, we discuss related studies in the literature. We focus on literature reviews, reports, and surveys that provide an overview of techniques that can be applied to automate the negotiation process.

Automated negotiation has received much attention over the past decade. The literature proposes approaches to automate the negotiation process to develop intelligent systems that have the human capability to negotiate autonomously. The proposed study in [64] highlights the framework of the negotiation process and focuses on techniques used to select negotiation strategies and choose a negotiation protocol to carry out the process. Moreover, it also provides the concepts of general terminology of the negotiation process such as *bilateral or multilateral negotiation, single issue or multi-issue negotiation*. The study explains attributes of the negotiation process; however, it lakes the state of the art as it mostly mentions the studies from the last decade. Comparatively, our study provides the state of the art for automating the negotiation process covering the literature for the last 6 years.

Bilateral negotiation is a scenario in which only two agents are involved in the negotiation. It is possible for the agents to either have full or partial information about each other or be unaware of each other. The literature review in [60] provides an extensive understanding of bilateral negotiation considering it as a game theory problem. It further divides the concept into cooperative bargaining, where bilateral agents have complete information about each other, and non-cooperative bargaining, where the agents have incomplete or zero information about each other. The study discusses several scenarios of bargaining for price and provides a better understanding of bilateral negotiation in economics and AI. However, it lacks the review of recent the state of the art and is limited only to the techniques used for bilateral negotiation. Our study covers the recent literature with a more general focus on automated negotiation involving the literature for bilateral as well as multilateral negotiation.

Complementing the previous study, the survey in [54] focuses on approaches for negotiation in multi-agent environments where the agents are considered self-interested. It also mentions the techniques for cooperative agents. The proposed study considers the negotiation time, efficiency, and simplicity of negotiation strategies as attributes to evaluate the decisions. For example, negotiation time measures the delay in reaching an agreement which causes more computational resources compared to the ones that reach an agreement early. Similarly, the efficiency of the decision can be evaluated by comparing the reward of all agents involved in the negotiation which should be equal for every agent to reach a successive agreement, and simplicity can be evaluated by computing the time duration for generating strategies. The proposed study mainly focuses on strategic negotiation. On the contrary, our systematic mapping study focuses on multiple goals for automating the negotiation process.

Preference elicitation is a requisite before starting the negotiation process. As mentioned in Section 2, the agents can finalize their private during the pre-negotiation phase. Besides that, preference elicitation is also useful when an autonomous agent negotiates on behalf of the human agent since the goal of the automated decision system is to assist humans. Hence, it is necessary for autonomous agents to accurately model user preferences. A survey of preference elicitation techniques is presented in [24]. The survey explains preference elicitation techniques, such as a value function that queries the user to rank the outcome of the value function and clustering that combines and compares the preferences of different users. Although the study provides some techniques for preference elicitation, it lacks the techniques presented in recent literature that focus on the agent's history of offers to represent users in automated negotiation.

A recent study published in [50] provides 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.

The study in [18] provides a review of intelligent agents in electronic negotiation systems. The study provides a detailed review of the types of agents that can be involved in the negotiation process, their life cycle, and of techniques that can be applied to automate the negotiation process. However, the study only reports selected applications of intelligent negotiation agents. Similarly, the authors of [51] propose a new model for the life cycle of a negotiation agent and map existing research to its constituents. The results of a closely related survey are reported in [9], focusing on techniques that can be used for opponent modeling. The authors also provide an in-deep discussion on how opponent models benefit negotiation agents. Differently from these studies, our work relies on a systematic process for the discovery of relevant literature in the field and provides a more complete overview of used techniques and research trends.

A recent survey [49] provides a review of machine learning techniques that can be used for bidding strategies in the electricity supply market. Similarly, the study in [31] provides a review of machine learning techniques for automated negotiation in the environmental resource management domain. In relation to the two studies above, ours is broader in scope, covering studies that apply negotiation to a variety of domains (see Section 5.2) and can possibly rely on negotiation techniques not grounded in machine learning (see Section 5.1).

In this section, we mentioned several literature reviews and reports. Although some of the studies are performed systematically, they do not include the recently published literature. Moreover, they also include studies that only theoretically discuss decision-making systems. In our mapping study, we focused on publications in the last 6 years, which provide a practical implementation of techniques that can be implemented for automating the negotiating process. In the next section, we describe the process we carried out for our systematic mapping study.

Table 1 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

4 Study design

For our systematic mapping study, we structured our research into three main phases, commonly employed in systematic literature studies [52, 88]: planning, conducting, and documenting.

Planning – During this phase, we realized (i) the need of performing a systematic mapping study on automated negotiation for agreement, (described in Section 3), and (ii) we defined the research questions (further discussed in Section 4.2.1).

Conducting – At this stage, we followed the required steps to perform this mapping study such as (i) searching for and selecting relevant studies for automated negotiation (Section 4.2), (ii) scrutinizing relevant studies and extracting data from each one following an analysis framework (Section 4.3), and (iii) synthesizing the main insights emerging from the data collected during the previous activity (Section 4.4).

Documenting – In the last stage, we finalized the process by (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, (ii) having a detailed discussion of possible threats to validity, and (iii) writing the final report (i.e., this article) which delineates the performed mapping study.

A complete replication package is publicly available to allow interested researchers to independently replicate and verify our study[1]. The package includes a comprehensive data extraction form, the raw extracted data, and the scripts employed for data analysis.

4.1 Research questions

The aim of this study is to help the research community to summarise 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 by using the Goal-Question-Metric perspectives (i.e., purpose, issue, object, viewpoint [22]). Table **1** shows the resulting outcome. We further divided our goal in the following research questions:

RQ1: What is the specific purpose of the negotiation?

As mentioned earlier, automated negotiation is the process where multiple parties communicate with each other and jointly reach an agreement to solve a problem. With this research question, we aim to identify and categorize the problems for which

[1] https://github.com/mashalafzal/Automated-negotiation-replication-package

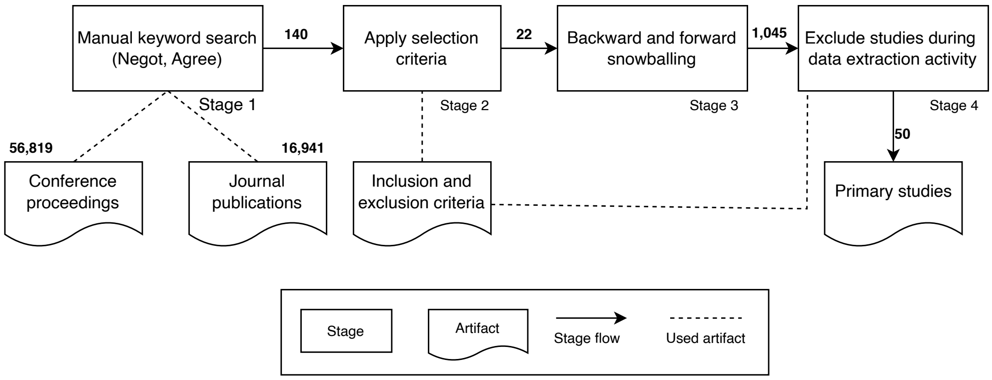

Fig. 2 The search and selection process of our study

negotiation is employed in the literature, to provide an overview of the problems that can be solved through negotiation, and its possible application domains.

RQ2: How is the negotiation process carried out?

This research question explores how the negotiation process is carried out. Specifically, we investigate what kind of techniques are applied to enable the negotiation, what inputs are needed, and what are the outputs obtained by agents involved in the process.

RQ3: What are the limitations of the current approaches, open issues, and future challenges?

Automated negotiation is a promising research topic. However, to reap its benefits, there are still limitations and deficiencies that need to be overcome to enable its practical application in a real-world scenarios. Hence, this research question focus on assessing and categorizing the limitations present in the current state of the art.

RQ4: What are the current research trends for automated negotiation?

A multitude of researchers are investigating automated negotiation techniques with different degrees of independence and different methodologies. By answering this research question, we aim at characterizing the scientific interest of the research community on automated negotiation in terms of relevant venues and contribution types.

4.2 Search and selection process

An overview of our search and selection process is shown in Figure 2. The process is responsible for the inclusion or exclusion of any potential study for this research. It is a multi-stage process whose steps are described below.

Manual keyword search – We have started our search and selection procedure by identifying the top-level venues for software engineering and artificial intelligence research. For conferences, we adopted the *GII-GRIN-SCIE-Conference-Rating*[2] ranking as a reference list and selected from it all conferences ranked *A* or higher in the domains of interest. *GII-GRIN-SCIE (GGS)* is a conference raking list initiated by a group of *Italian* and *Spanish* Professors in the domain of *computer engineering and computer science.* It provides the bibliometric approach for the conference proceedings that are not available in *SCOPUS* database. For journals, we used the *SCOPUS* database[3] as a reference and selected from it all potentially relevant journals by searching from the top 10% journals in 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 resulted in the identification of 24 conferences and 22 journals in which to search in-depth for studies potentially relevant to our research. The full list of selected venues is available in Table 12.

Inside these venues, we performed a keyword-based search, using as keywords the words *negot* and *agree*. These keywords have been selected as they represent the root form of words frequently found in titles of studies in the field of automated negotiation (i.e., *negot* for negotiate and negotiation, *agree* for agreement). This step was carried out inside the Computer Science Bibliography from the University of Trier (i.e., DBLP [59]), considering a time frame that goes from the 1st of January 2017 to the 30th of June 2022 for each of the venues selected at the previous step. This search considered a total corpus of 73,760 studies, out of which 56,819 were the results of conference proceedings and 16,941 belong to journal publications. The selected keywords were found in 140 potentially relevant studies, where 118 studies have been selected as a result of searching in conference proceedings and 22 studies have been selected as a result of searching journals.

Studies selected during this keyword-based search were further classified and sorted according to the parameters of our inclusion and exclusion criterion discussed below. It is worth mentioning that this step was not only focused on extracting *all* relevant studies but, as suggested in [87], we concentrated on extracting potential relevant studies to utilize as a basis for a subsequent snowballing procedure, discussed in the following.

Apply selection criteria – The resulting studies were further filtered out according to inclusion and exclusion criteria discussed in Section 4.2.1. Following the guidelines in [72, 97], we carried out the selection process in a time-efficient and objective manner, employing an adaptive reading depth procedure as it was not necessary to read the full text of approaches that did not qualify. Studies that didn't fulfill the inclusion and exclusion criteria were eliminated, yielding a new total of 22 primary studies. This reduction in the number of results is to be expected, as the selected venues are broad in scope, covering varied areas of computer science and artificial intelligence.

Backward and forward snowballing – To have a comprehensive set of studies representative of the literature of the field, we applied *backward and forward snowballing* [87]. For snowballing, we also applied the keyword-based search using *negot*

[2] https://scie.lcc.uma.es:8443/
[3] https://www.scopus.com/sources

and *agree* keywords followed by the selection criteria. We used *backward snowballing* to evaluate the studies which are cited by the set of our selected relevant studies. Backward snowballing allowed to identify studies related to our study's aim which were not published in the selected venues. This stage resulted in a total of 766 studies. Later, we applied the keyword-based search and inclusion and exclusion criterion to these results and 19 studies have been selected as a result of backward snowballing.

Furthermore, *forward snowballing* [87] has also been applied by analyzing the studies which have cited the set of our selected potential studies. Through this step, we figure out all those new and relevant studies which were not included in conference proceedings or journal issues. Forward snowballing yielded the total number of 279 studies which were also further scrutinized according to the keyword-based search and inclusion and exclusion criterion mentioned below in section 4.2.1. 22 studies have been selected as the result of forward snowballing.

To carry out both backward and forward snowballing, we have utilized *Google Scholar*[4] database. Following the inclusion and exclusion criterion, we have figured out that 41 out of 1,045 results of backward and forward snowballing were actually relevant for our study. Moreover, out of 41, 10 studies were already included in the set of of our selected studies hence, a total of 31 studies were selected from the snowballing process, along with 22 primary studies scrutinised as per our inclusion and exclusion criterion applied on the results of initial search.

Exclude studies during data extraction activity – During the data extraction, we also paid attention to the duplicate studies present in the set of selected studies, i.e., papers that were found to be the same but published in multiple venues. For instance, [14] and [15] focus on opponent modeling for counter offer generation using deep learning. These studies were merged as PS49 (a) and PS49 (b) as both studies propose the same technique, published by the same authors in different venues. A total of 3 pairs of studies were merged this way, resulting in a final set of 50 primary studies selected for further analyses. The merged studies are counted as one throughout the paper except for Section 5.4 and Section 6, where the studies are counted separately according to the publication year, venue, and inter parameter mapping. The final list of selected primary studies is available in A.

4.2.1 Selection criteria

In order to minimize the possibility of biases, we followed well-known guidelines to conduct systematic literature reviews [52] 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. Notice that, any study which satisfied *all* inclusion criteria was included. However, any of the studies which satisfied *at least one* of the exclusion criteria was discarded. The inclusion and exclusion criterion are listed below.

Inclusion Criteria

I1 Studies in which autonomous systems take decisions as a result of agreements reached through negotiation processes.

[4]https://scholar.google.com/

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 Studies not peer-reviewed, such as preprints and technical reports.
E3 Secondary studies, such as surveys and literature reviews.
E4 Studies lacking a technical description of the proposed method.
E5 Studies not written in English language.

4.3 Data extraction

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

To perform a rigorous data extraction process, a predefined data extraction form was designed prior to beginning the data extraction process. The data extraction form structure reflects the various categories of the classification framework. The classification framework is composed of four distinct parts, one for each research question of our study. The overview the classification framework, and respective parameters, is reported in Table 2, whereas the definition and values of each specific parameter is given alongside the discussion of extracted data in Sections 5.1, 5.2, 5.3, and 5.4.

To carry out the data extraction, all of the selected primary studies were analysed by two researchers. The two researchers worked cooperatively to construct a record for each analysed study that summarizes the extracted information and allows for further analysis. Disagreements among the two researchers were discussed and solved with the intervention of a third researcher.

Table 2 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 Type of agent involved in negotiation
RQ3	Limitations, Future Study	Limitations and future research
RQ4	Research Trends	Year of publication Publication venue Publication venue type

4.4 Data synthesis

This stage deals with aggregating and summarizing the data extracted from the primary studies as suggested in [48]. The main goal during this phase is understanding, analyzing, and characterizing the current state of the art of research for automated negotiation.

We further divided the process of data synthesis into two stages, i.e., vertical and horizontal analysis. For the *vertical analysis*, we examined the extracted data to look for possible trends and patterns for each parameter of our classification framework. Instead, for the *horizontal analysis*, we considered parameters in pairs, to discover possible relationships across parameters in collected data. For this purpose, we utilized contingency tables[5].

In both phases, we performed a combination of content analysis (for categorizing and coding the studies under broad thematic categories) and narrative synthesis (mainly for explaining results in detail and interpreting the findings). During the horizontal analysis, we used contingency tables for evaluating the actual existence of inter-parameter relations.

5 Results

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

5.1 Specific Purpose (RQ1)

In the following, we discuss the results for parameters related to the purpose for which negotiation is employed.

Negotiation purpose – The negotiation purpose represents the principal goal for which the negotiation techniques were conceived. By carefully analyzing the primary studies, four main purposes categories emerged from the keywording process: *reward maximization*, *opponent modeling*, *agreement for cooperation*, and *preference elicitation*. Table 3 summarizes the primary studies divided by their goal and, in the following, we discuss each of the four goals in detail. Some of the studies focus on more than one goal which is also given in Table 3.

Example: The primary study PS49, proposes an approach to learn opponent strategies using deep neural networks for autonomous negotiation in e-Commerce. Moreover, it generates counter offers based on the learned strategies of the opponent to secure more rewards compared with its preferred value. Similarly, other studies also focus on more than one goal and are represented in Table 3 under multiple categories of the purpose.

Reward maximization – The majority of the primary studies (40/50) propose techniques aimed at maximizing the reward tied to the offers generated by the agents. Particularly, 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 and the time elapsed since the beginning of the negotiation.

Example: The authors of PS8 argue that agents can increase their reward by taking advantage of the negotiation context, i.e., the set of facts, events, trends, and special

[5] For our horizontal analysis, we applied the same process as the one in [6]

Table 3 Studies grouped by purpose

Purpose	Studies #	Primary studies
Reward maximization	40	PS2, PS5, PS6, PS7, PS8, PS9, PS10, PS11, PS12, PS13, PS14, PS16, PS17, PS19, PS20, PS21, PS22, PS23, PS24, PS25, PS26, PS27, PS28, PS29, PS30, PS31, PS32, PS34, PS35, PS36, PS37, PS38, PS39, PS41, PS42, PS43, PS45, PS46, PS47, PS49
Opponent modeling	15	PS4, PS6, PS7, PS11, PS14, PS18, PS19, PS21, PS23, PS33, PS40, PS43, PS44, PS49, PS50
Agreement for cooperation	6	PS1, PS3, PS5, PS9, PS15, PS48
Preference elicitation	6	PS24, PS27, PS32, PS34, PS36, PS38

circumstances that surrounds the negotiation. To this end, they propose a context-aware negotiation agent that learns through self-play and reinforcement learning how to use key contextual information to gain a competitive edge over other agents.

Opponent modeling – Information about the opponents is essential to improve automated negotiation strategies [43]. Understanding the behaviour of opponents is referred to as opponent modeling and helps in finding a more successful outcome of the negotiation for both parties involved. A total of 15 primary studies propose techniques that aim to improve the current state of the art for opponent modeling.

Example: The primary study PS19 focuses on opponents' history for offer generation in order to learn how to maximize the chances of acceptance of an offer during negotiation. It proposes a novel technique for automated negotiation agents where an agent uses Q-learning to develop a bidding strategy until the agreement is reached between the two parties involved in the negotiation process.

Agreement for cooperation – While negotiation is often employed with the goal of maximizing utility, other studies focus on reaching an agreement between autonomous agents to perform a task cooperatively. We group the latter studies under this goal. A total of 6 primary studies fall in this category.

Example: The study PS5 introduces an approach called distributed emergent agreement learning (DEAL). It enables agents suggest agreements to other agents in order 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.

Preference elicitation – In the context of automated negotiation, designing agents that can effectively acquire and integrate users' preferences into their own decision-making is an open research direction. We group under this goal studies that propose novel preference elicitation methods, to better capture the users' preferences, in both an autonomous or assisted manner. Preference elicitation lies in the pre-negotiation phase (as discussed in Section 2), and can be helpful in having autonomous agent that more closely respect the wishes of users [91]. A total of 6 primary studies fall into this goal.

Example: PS36 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.

Application Domain – This parameter is used to represent the field of application for the techniques proposed by the primary studies. In Table 4 a breakdown of the studies grouped by application domain is provided. A total of 27 studies focus on techniques to negotiate on the price of a product or a service. Hence, we summarize the application domain of these studies as *economics*. A total of 14 studies instead generate offers without considering a specific domain, as they propose generic techniques that can be used to negotiate in any environment, depending on the goal of the agent. Thus, these techniques have been labeled as having a *generic/unspecified* domain. Moreover, 6 primary studies propose techniques for a *cooperative environment*, where the agents negotiate in order to perform a task cooperatively and share the reward afterward. Conversely, 2 studies focus on a *competing environment*, in which the agents consider each other as opposing players and generate offers accordingly. Finally, a single study focuses on the *privacy* domain, in which the object of the negotiation is the access permissions granted to social network apps on behalf of the human user.

Table 4 Studies grouped by application domain

Domain	Studies #	Primary studies
Economics	27	PS2, PS8, PS10, PS12, PS14, PS16, PS17, PS20, PS22, PS26, PS27, PS28, PS30, PS31, PS32, PS34, PS35, PS37, PS38, PS39, PS41, PS42, PS43, PS45, PS46, PS47, PS49
Generic/unpecified	14	PS6, PS11, PS13, PS18, PS19, PS21, PS23, PS24, PS25, PS29, PS33, PS40, PS44, PS50
Cooperative environment	6	PS1, PS3, PS5, PS9, PS15, PS48
Competing environment	2	PS4, PS7
Privacy	1	PS36

5.2 Techniques, Input and Output (RQ2)

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

Negotiation inputs – This parameter is used to summarize the inputs required by the techniques proposed in the primary studies, reported in Table 5. The majority of the studies (32) take as input *reserved, preferred and initial price values* required in order to negotiate on the price of products or services. Another commonly used input is the *opponents' offers history*, employed by 15 primary studies. This information allows to improve on the generation of offers by considering how opponents have acted in the past. Similarly, 6 studies take as input the history of offers of the user on behalf of which they are negotiating, in order to understand his behaviour and preferences. Furthermore, 6 primary studies require as input previous *arguments and dialogues* from which infer information from. Two primary studies rely on input rules for the negotiation process, which the agents follow to generate offers.

Example – In PS2, the agents negotiate for purchasing or selling a laptop. The lowest price for buying the laptop and the highest price for selling it are already fixed before starting the negotiation as reserved values. 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 reserved value of the seller agent, then the deal is automatically accepted.

Example – In PS3, the agents negotiate to perform a task cooperatively and divide the reward. The study uses reinforcement learning where the agents learn about the reward for cooperation to negotiate and reach an agreement. However, it additionally uses a language channel through which the agents can exchange strings or symbols for communication.

Table 5 Studies grouped by input

Inputs	**Studies #**	**Primary studies**
Reserved, preferred and initial price values	32	PS1, PS2, PS3, PS8, PS9, PS10, PS12, PS13, PS14, PS15, PS16, PS17, PS18, PS20, PS25, PS26, PS27, PS28, PS29, PS30, PS31, PS34, PS35, PS37, PS38, PS39, PS41, PS42, PS45, PS46, PS47, PS48
Opponents' offers history	15	PS4, PS6, PS7, PS11, PS14, PS18, PS19, PS21, PS23, PS33, PS40, PS43, PS44, PS49, PS50
User's offers history	6	PS24, PS27 PS32, PS34, PS36, PS38
Arguments and dialogues	6	PS1, PS3, PS5, PS20, PS22, PS30
Rules	2	PS9, PS29

Negotiation outputs – This parameter is used to summarize the outputs of the negotiation process. In Table 6, we present the output for all primary studies. With regards to this parameter, the studies can be partitioned in two groups. A first group of 35 studies produce as output of the negotiation the final accepted offer and the reward associated with that offer. Studies in the second group (15) instead produce as output counter offers as final offers by specifically analyzing the opponent offers to submit to the other negotiating party in order to secure more rewards.

Techniques used for automation – We present below the table of all techniques used in our selected primary studies for automating the negotiation process in Table 7.

Table 6 Studies grouped by output

Outputs	Studies #	Primary studies
Final offers, rewards for agreement and cooperation	35	PS1, PS2, PS3, PS5, PS8, PS9, PS10, PS12, PS13, PS15, PS16, PS17, PS20, PS22, PS24, PS25, PS26, PS27, PS28, PS29, PS30, PS31, PS32, PS34, PS35, PS36, PS37, PS38, PS39, PS41, PS42, PS45, PS46, PS47, PS48
Counter offers by analyzing opponent offers	15	PS4, PS6, PS7, PS11, PS14, PS18, PS19, PS21, PS23, PS33, PS40, PS43, PS44, PS49, PS50

The total of techniques mentioned in the table is greater than the total number of primary studies as some studies employ more than one technique to automate the negotiation process.

Example – In PS4, two opponent agents follow alternative offer protocol to generate offers one by one for automated negotiation. The agent uses deep reinforcement learning to learn the opponent's strategies and then utilizes Bayesian learning to select one offer from the available offers to the agent. The study focuses on opponent modeling to learn about the opponent and generate counter-offers to end the negotiation by reaching an agreement or disagreement.

Type of agent involved in negotiation – For this parameter, we looked for the studies which suggest the approaches implemented on autonomous agents or at least involve one autonomous agent. We eliminate the studies which consider only human agents. Table 8 shows the division of our primary studies into two categories (i) studies involving only autonomous agents, and (ii) studies involving one human agent and another autonomous agent.

Example – In PS1, the autonomous agent negotiates with other autonomous agents to form a team and complete the task without any human input as a cooperative game problem. The agents jointly perform the task and divide the final reward by communicating autonomously through a language channel using strings. However, in PS35, two human agents negotiate with an autonomous agent over the price of products. The human agents serve as customers while the autonomous agent serves as a seller. Each agent negotiates to maximize their reward in exchange for coins to purchase or sell the products and reach an agreement.

5.3 Limitation and Future Study (RQ3)

In the following, we discuss results for parameters related to the limitations found in the state of the art and future research directions.

Limitations and future research – The focus of the studies presented in the literature is based on collecting rewards where only two agents negotiate with each other. A total of 25 studies follow a bilateral negotiation strategy where one agent can only negotiate with one other agent.

Table 7 Primary studies by used technique

Technique	Studies #	Primary Studies
Alternative Offer Protocol	23	PS2, PS4, PS6, PS8, PS10, PS11, PS16, PS17, PS18, PS19, PS25, PS27, PS31, PS33, PS36, PS37, PS38, PS39, PS41, PS42, PS45, PS46, PS50
Reinforcement Learning (Q-Learning and DRL)	13	PS1, PS2, PS3, PS4, PS5, PS6, PS8, PS10, PS11, PS15, PS18, PS19, PS23
Gaussian Probability	5	PS7, PS21, PS24, PS32, PS40
Bayesian Learning	5	PS4, PS14, PS21, PS44, PS50
Neural Networks	4	PS14, PS37, PS43, PS49
Fuzzy Systems	4	PS29, PS34, PS45, PS47
Monte Carlo Tree Search	3	PS9, PS21, PS48
Long Short-Term Memory Networks (LSTM)	2	PS1, PS30
Linear Programming	2	PS27, PS28
Argumentation Framework	2	PS20, PS22
Linear Regression	2	PS13, PS39
Genetic Algorithm	1	PS12
Markov Decision Process	1	PS24
Non-Linear Regression	1	PS14
Angle based Similarity Approach	1	PS17
Heuristic Algorithm	1	PS26
Equilibrium Strategies	1	PS35
Logistic Regression	1	PS37
Multi bipartite gradient descent search	1	PS33

Example – The primary study PS38 proposes a technique that can be applied to only two autonomous agents that negotiate for a price where one agent is represented as a buyer and another agent is represented as a seller. This limitation can be addressed by proposing techniques for multilateral negotiation where multiple agents can negotiate with multiple opponents such as multiple buyers negotiating with the same seller or vice versa.

Another limitation in the state of the art is the negotiation for a single issue. A total of 19 studies propose techniques that only focus on negotiation for a single issue, e.g., negotiation only for the price as given in the same example above. This limitation can be addressed by proposing techniques for multiple real-life issues to develop intelligent systems that can be deployed in a real-world environment.

Moreover, 16 studies consider improving the proposed technique for better performance.

Table 8 Studies grouped by agent type

Agent Type	Studies #	Primary Studies
Autonomous agents	38	PS1, PS2, PS3, PS4, PS5, PS6, PS7, PS8, PS9, PS11, PS14, PS15, PS16, PS17, PS18, PS19, PS21, PS22, PS23, PS25, PS27, PS30, PS31, PS33, PS34, PS37, PS38, PS39, PS40, PS41, PS42, PS43, PS44, PS45, PS46, PS48, PS49, PS50
Human and autonomous agents	12	PS10, PS12, PS13, PS20, PS24, PS26, PS28, PS29, PS32, PS35, PS36, PS47

Table 9 Studies grouped by limitation

Limitation	Studies #	Primary studies
Bilateral negotiation	25	PS2, PS4, PS6, PS7, PS8, PS10, PS11, PS16, PS17, PS18, PS19, PS25, PS27, PS31, PS33, PS34, PS37, PS38, PS44, PS45, PS46, PS47, PS48, PS49, PS50
Single issue negotiation	19	PS8, PS12, PS16, PS17, PS20, PS22, PS26, PS27, PS28, PS31, PS34, PS35, PS38, PS39, PS41, PS42, PS46, PS47, PS49
Improve proposed methods	16	PS1, PS3, PS5, PS8, PS9, PS15, PS21, PS23, PS30, PS32, PS34, PS35, PS36, PS39, PS41, PS43
Involves human agent	12	PS10, PS12, PS13, PS20, PS24, PS26, PS28, PS29, PS32, PS35, PS36, PS47
Time dependent negotiation	6	PS6, PS14, PS18, PS40, PS42, PS46

Example – The primary study PS8 uses Q-learning where two agents negotiate the price of electricity. The study suggests using inverse reinforcement learning for the same problem to better imitate human behavior in autonomous negotiation systems. Similarly, other studies consider changes in the proposed approaches.

For our mapping study, we consider studies that involve autonomous agents, hence there are still 12 studies that limit involving one human agent along with another autonomous agent in the negotiation process as mentioned in Table 8. This can be further addressed by proposing techniques that can be deployed on autonomous agents for automated negotiation.

In Table 9, we present the limitations found in the literature. It is noticed from the proposed research that the main idea behind the studies in the state of the art is focused on reward maximization. It will be interesting to propose techniques for automated negotiation where the agents negotiate real-life issues. For instance, the negotiation between two autonomous vehicles for one available parking lot, the negotiation between intelligent agents for automated auctions, and the negotiation between intelligent agents in healthcare. Another additional example can be making an ethical decision that involves no breach of privacy of passengers. Although nowadays the research community is focused on embedding ethics into automated decision making [63, 94], we believe that no research is available that in real immerses the concept of ethics into automated decision making, which opens the doors for future research. We further discuss the need for an ethical autonomous system in Section 7.

5.4 Research Trends (RQ4)

In the following, we discuss results for parameters related to publication year and venues.

Year of publication – We searched for publications for a period of 6 years, starting from January 2017 to June 2022. In Figure 3, we present the overview of the ratio of our selected publications. Some studies from snowballing were published before 2017 and satisfied the keyword-based search and inclusion criteria, hence those studies were included and presented collectively as shown below in Figure 3.

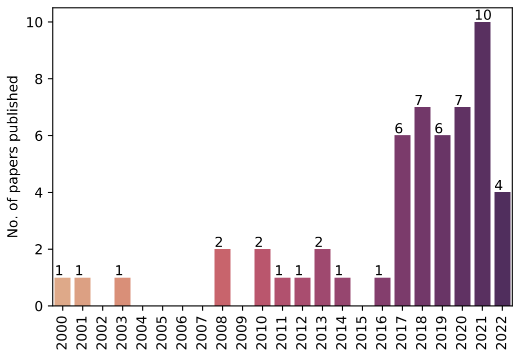

Fig. 3 No. of primary studies grouped based on publication year

Publication venue – As mentioned in Section 4.2, we have selected top-level venues for conference proceedings and journal publications for this mapping study. The list of our selected venues is shown in 12. In Figure 4, we present the division of the total number of studies published in the same venue. From a total of 24 conferences and 22 journals, the AAMAS conference results to be the most targeted venue where (13/53) studies were published followed by (6/53) published at the IJCAI conference. Other venues which included one paper in each were counted and represented together.

Publication venue type – The search and selection process for this research includes conference proceedings and journal publications. However, snowballing resulted in some relevant studies from the workshop, hence they were also included. As shown below in Table 10, the number of conference proceedings and journal publications is almost the same . A total of 26 out of 53 studies are results of conferences, and 23 out of 53 studies are results of journals, where the remaining 4 are papers published in workshops.

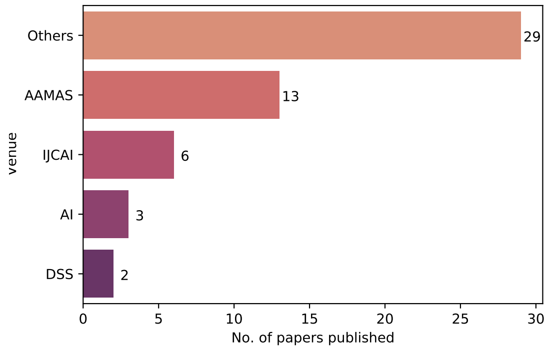

Fig. 4 Most targeted publication venues

Table 10 Studies grouped by venue type

Venue type	**Studies #**	**Primary Studies**
Conference	26	PS2, PS5, PS6, PS7, PS9, PS10, PS11, PS13, PS19, PS20, PS21, PS22, PS23, PS24, PS25, PS30, PS32, PS33, PS36, PS40, PS41, PS44, PS47, PS48a, PS48b, PS49a
Journal	23	PS3, PS8, PS12, PS14, PS15, PS16, PS17, PS18, PS27, PS28, PS29, PS31, PS34, PS35, PS37, PS38, PS39, PS42, PS45, PS46, PS49b, PS50a, PS50b
Workshop	4	PS1, PS4, PS26, PS43

6 Orthogonal findings

In this section, we discuss the results of data synthesis through horizontal analysis. As mentioned in Section 4.4, we utilized contingency tables to extract inter-parameter relationships among pairs of parameters in our classification framework. We computed and analyzed contingency tables for all pairs of parameters. However, for reasons of space, below we report only on the most relevant pairs. The total number of studies for inter-parameter relation mapping as a result of the contingency tables can be greater than the actual number of studies, i.e., 53, as some studies focus on more than one parameter and are counted separately with the mapping of specific parameters.

Application domain - Negotiation purpose – Economics is the most focused application domain in the literature. The majority of studies that propose techniques for reward maximization consider the application domain of the studies as economics. A total of 28 studies that focus on reward maximization for negotiation purposes consider economics as the application domain. Generic is the second most focused domain, with 9 studies that perform reward maximization for this purpose. The remaining application domains, such as cooperative environment, competing environment, and privacy, are focused on by only a small set of studies. This emphasis on economics reveals the need for a general-purpose agent, able to negotiate in multiple domains and for multiple purposes, as to enable the adoption of automated negotiation in the real world. Indeed, real-world scenarios are complex and involve negotiating for varied resources that cannot always be reduced to abstract economic scenarios [62].

Limitation - Negotiation purpose – Bilateral and single-issue negotiations are the most observed limitations found in the selected primary studies. Indeed, the majority of the studies that focus on reward maximization present the limitation that the agents negotiate with only one opponent agent and only for a single kind of issue. A total of 20 studies that perform reward maximization suffer from negotiating for a single issue as a limitation, whereas 19 studies that focus on reward maximization declare bilateral negotiation as an issue. The studies that focus specifically on preference elicitation (3 studies) to represent the human user during negotiation suffer from the limitation that the user still has to be involved in the negotiation process, which needs to be resolved to achieve fully automated negotiation approaches. Moreover, even if the limitation of the single opponent is common in all studies that perform negotiation for multiple purposes, the single issue limitation is found only in 2 studies that focus on opponent modeling. This is due to the fact that these studies rely on the history of offers generated by an opponent agent to generate counteroffers. Therefore, the more issues are negotiated, the better the agent will be at generating strategies by learning the offers of the opponent.

Technique used - Negotiation Purpose – Alternative offer protocol is the most utilized approach in the literature by studies that perform negotiation for multiple purposes. The negotiation protocol is defined as a set of rules to specify the order in which offers are generated during the negotiation, and with the alternative offer protocol, the participating agents take turns in generating offers during negotiation. Moreover, as reward maximization is the most focused negotiation purpose observed in the literature which involves negotiation between two agents, hence, alternative offer protocol is the most utilized approach in the studies that perform negotiation for reward maximization. A total of 19 studies use this approach that perform negotiation for reward maximization and 9 studies for opponent modeling. The other most utilized approach in the literature is reinforcement learning, which is utilized by 8 studies focusing on negotiation for reward maximization and 7 studies focusing on opponent modeling. The remaining techniques mentioned in the literature are utilized by studies with a small count as shown in Table 7.

Technique used - Application Domain – As economics is the most observed application domain in the literature, it is the purpose for which most techniques are used. In the economics domain, the alternative offer protocol is the most utilized technique, with 14 studies. It is followed by neural networks (5), reinforcement learning (3), and fuzzy logic (3). Most of the other techniques mentioned in Table 7 are used by a single study for economics. The other most observed application domain is generic, which utilizes the alternative offer protocol for 8 studies, reinforcement learning for 5, and Bayesian learning for 4 studies. We provide the mapping of techniques used with the application domain as a result of our horizontal analysis in the replication package[6].

Negotiation inputs - Negotiation Purpose – The agents provide reserved and preferred values to initialize the negotiation process as mentioned in Section 5.2. We count them collectively here as offers with values for reward, which are most utilized by the studies that perform negotiation for reward maximization. A total of 27 studies use offers for reward as input for the negotiation process for reward maximization. The offers generated by the opponent agents are also used as input by most of the studies to learn and generate counter offers. A total of 18 studies use opponent offers as input for opponent modeling, and 11 studies use these offers for reward maximization. For preference elicitation, 6 studies utilize the history of the user as input for the negotiation process. In 3 studies, when the agents negotiate for cooperation, additional dialogues are used as input along with offers for better explanation. In 2 studies, a set of rules is used as input for the negotiation process to propose offers for reward maximization.

7 Discussion and future research challenges

In previous sections, we discussed the overview of the state of the art. In this section, we discuss research challenges that we concluded from the state of the art as our understanding for future research directions.

Is there more than economics for automated negotiation? Referring to Table 4, it is evident that most of the studies that propose automated negotiation techniques lie in the economics domain, in which agents negotiate for the price of an item being exchanged or a service being provided. One of the possible reasons why economics is the most observed domain is the encoding of the data that an agent needs to generate negotiation offers. Indeed, when negotiating for a price, the agents only need to encode the preferred and reserved price values that the agent wants to bid on and receive to maximize its reward. However, negotiating for resources of other kinds would require encoding different types of data, such as dialogues [26], rules [66], texts, images, or even data from sensors. One example is the work presented in PS36, in which the autonomous agent grants access to user data on her smartphone to an online service in exchange for a monetary reward. The agent negotiates the types of data to share, learning the user privacy preferences from the history of the previous interaction with other services. Hence, considering only prices reduces complexity during the negotiation process. We hypothesize that this is the reason why the economics setting is the most frequently considered by studies in the literature. However, to make such agents useful in many real life scenarios, it is important to develop intelligent autonomous agents able to negotiate in diverse domains, leveraging heterogeneous kinds of information.

Is it possible to have a general-purpose automated negotiating agent? As presented in Table 4, 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

[6] https://github.com/mashalafzal/Automated-negotiation-replication-package

generalize its behavior and adapt to multiple environments and resource types. An initial effort towards a general-purpose agent is the work by Lin and colleagues [61, 62], in which the authors provide a framework to assist in the design of general-purpose negotiating agents, i.e., agents that "*can self-adapt in multiple environments by negotiating with other agents on real-life issues*". While innovative and thought-provoking, the proposed framework hardly fills the gap in the literature as agents built with the proposed framework exhibit severe limitations, such as the inability to negotiate with human negotiators. Hence, the challenge of a domain-independent autonomous agent capable of generalizing her/his behavior to negotiate in diverse environments is still relevant.

Can we remove humans from the loop? As displayed in Table 8, there is a considerable number of studies that consider the negotiation between an autonomous agent and an human agent [40]. In addition, in some studies, the human agent controls the decision of the autonomous agent, being able to change the decisions that the autonomous agent takes on her behalf [8].

To fully remove humans from the loop, giving autonomous agents full control, it is necessary to develop trustworthy autonomous agents that replicate human behavior and make ethical decisions even when things go wrong [92]. Indeed, human trust involves expectations of equality, justice, and fairness in the decision-making process [71], and the evaluation of such intelligent autonomous systems needs to minimize the risks that are posed to society when biases are introduced in the automated decision-making process [82]. More guidance is provided by the Ethics Guidelines for Trustworthy AI of the EU High-Level Expert Group on AI [42] that described the requirements that an AI system should satisfy to be considered ethical, among which: (i) respecting the rule of law; (ii) being aligned with agreed ethical principles and values, including privacy, fairness, and human dignity; (iii) ultimately keeping the humans in control, and (iv) being robust and safe so that system's behaviour remains trustworthy even if things go wrong. While these recommendations are aimed at more general purpose AI systems, we believe that they are relevant for automated negotiation systems, especially considering the increasing importance that automated negotiation will acquire in a world of interacting autonomous systems. Hence, an open research direction is on how to introduce these principles in automated negotiation systems, to ultimately remove humans from the loop.

What are the growing research trends in the literature? From the results of RQ4, previously presented in Section 5.4, it is noticeable that automated negotiation is a topic that is attracting a growing interest in the literature, with noticeable increase in the number of studies published on the subject in the more recent year. In addition, as shown in Table 12, the most popular venues for works in the domain of automated negotiation are AI-focused ones. If, on the one hand, this can be motivated by the growing interest that AI technologies are receiving in recent years, on the other hand it highlights that automated negotiation could play a central role in future AI-based autonomous systems. Indeed, future autonomous systems will be able to represent humans and make decisions on their behalf without their intervention and will interact with other humans or autonomous systems [68]. Hence, in the future, these systems could take advantage of negotiation techniques to achieve more equitable and fair interactions with humans and other systems.

8 Threats to validity

In this section, we discuss the quality of the data and threats to the validation of primary studies.

At first, we defined a research protocol to verify the high quality of the acquired data, i.e., the keyword-based selection of the primary studies used for this mapping study. The research protocol was established before proceeding with the data collection and was designed by following the guidelines for planning the systematic mapping study from [48]. As presented in Section 4, we rigidly complied with the research protocol during the evolution of the proposed study. In addition, we combined and executed all steps involved in the research protocol (e.g., study design, search and selection, data extraction, and data analysis) together in teams to additionally guarantee the quality attributes of the established research protocol. We conducted this activity to reduce the chances of bias by brainstorming in the team. Threats to validity can sometimes be unpreventable.

In the remaining of this section, we further discuss threats to validity in the context of our study and how we did our best to diminish them.

External Validity. This stage deals with validating the risk of quality assurance [88], i.e., whether the proposed study concludes the state of the art literature or not. To mitigate this type of risk, we selected top-level venues for searching publications where we manually applied keyword-based search and selection processes for conference proceedings and journal publications. Later, this activity was further extended by applying forward and backward snowballing to have a comprehensive set of studies representative of the literature of the field. Furthermore, we only extracted peer-reviewed publications and eliminated short papers, preprints, editorials, etc. This process was applied to maintain quality, as peer-reviewed studies are an essential item for high-grade publications. Subsequently, we applied a set of inclusion and exclusion criteria, which led to further refinement of the proposed study.

Internal Validity. This stage deals with validating the risk related to the study design [88]. To mitigate this type of risk, we established a research protocol and a classification framework. The classification framework is designed and strictly followed as detailed in Section 4, where the design of our study is presented from a methodological point of view. The researchers involved in the proposed study have independently followed the framework to adopt fairly evaluated descriptive statistics of the research.

Construct Validity. In this stage, we focused on ensuring the justification and compatibility of the primary studies with the research questions [88]. To ensure that, we manually extracted the literature from top-level venues related to computer science and applications, we additionally applied forward and backward snowballing. Subsequently, keyword-based search and inclusion and exclusion criterion were applied to the results of snowballing to extract studies that focused on the goal of the research. This was performed by two researchers by randomly choosing a set of studies and evaluating them to confirm the resemblance of the evaluation as suggested in [88].

Conclusion Validity. In this stage, the focus is to ensure the validity of the conclusion derived based on primary studies [88]. To do that, data extraction and analysis are carried out considering previously established research protocol. Our research protocol is specifically established to focus on data collection to justify the research questions that helped reduce any bias related to data extraction and analysis. It further helped to ensure that the obtained data is useful to answer our research questions. We followed the guidelines from [52, 72] to diminish the risk regarding the validity of the conclusion to ensure the transparency of our research.

9 Conclusion

The proposed systematic mapping study (SMS) is focused on the most relevant studies that allow us to identify the specific purpose of the negotiation and the list of techniques and approaches applied to automate the negotiation process. For this purpose, we extracted 53 primary studies from 73,760 relevant studies through a rigorous selection process from the top-ranked publication venues. We applied keyword-based search to extract relevant studies from 24 conferences and 22 journals for 6 years from 2017 to 30 June 2022. We follow the precise inclusion and exclusion criterion to include only studies that focus on the practical implementation of the techniques proposed for automated negotiation.

We designed a classification framework that helps identify the specific purpose of the negotiation, analyze inputs and outputs needed for the negotiation process, and extract the list of techniques applied to automate the negotiation process. In addition, we discuss the limitations of the state of the art and future research directions. The key results of our systematic mapping study have been presented by introducing (i) a blend of content analysis and narrative synthesis (vertical analysis) and (ii) a correspondence analysis through contingency tables (horizontal analysis). This mapping study focuses on helping the research community find potential studies published in the domain of automated negotiation that also consider practical implementation aspects.

To the best of our knowledge, no such research as our systematic mapping study is available that introduces a set of potential studies regarding automated negotiation which provides the practical implementation details of the techniques proposed for automated negotiation in the last 6 years. Hence, we believe that the proposed systematic mapping study establishes a valuable asset for the academic and research community in the wide spectrum of automated systems that involve intelligent agents for communication to reach an agreement and autonomously solve the problem.

Competing Interests

The authors declare that they have no competing interests.

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A Primary studies

Table 11: Primary studies

ID	Title	Author	Year
PS1	Coalitional Negotiation Games with Emergent Communication [37]	Xiaoyang Gao, Siqi Chen, Lin Jie, Yang Yang, Haiying Wu, and Jianye Hao.	2022
PS2	Deep Learnable Strategy Templates for Multi-Issue Bilateral Negotiation [16]	Pallavi Bagga, Nicola Paoletti, and Kostas Stathis.	2022
PS3	Deep reinforcement learning with emergent communication for coalitional negotiation games [26]	Siqi Chen, Yang Yang, and Ran Su.	2022
PS4	A Bayesian Policy Reuse Approach for Bilateral Negotiation Games [38]	Xiaoyang Gao, Siqi Chen, Qisong Sun, Yan Zheng, and Jianye Hao.	2022

PS5	Distributed Emergent Agreements with Deep Reinforcement Learning [78]	Kyrill Schmid, Robert Müller, Lenz Belzner, Johannes Tochtermann, and Claudia Linhoff-Popien.	2021
PS6	An Autonomous Negotiating Agent Framework with Reinforcement Learning based Strategies and Adaptive Strategy Switching Mechanism [79]	Ayan Sengupta, Yasser Mohammad, and Shinji Nakadai.	2021
PS7	Convergence of probabilistic automatic negotiation: mutual maximum likelihood estimation [85]	Koji Tsumura	2021
PS8	A context-aware approach to automated negotiation using reinforcement learning [56]	Dan E Kröhling, Omar JA Chiotti, and Ernesto C Martínez	2021
PS9	Exploring Monte Carlo Negotiation Search with Nontrivial Agreements [66]	Elijah Alden Malaby and John Licato.	2021
PS10	A deep reinforcement learning-based agent for negotiation with multiple communication channels [39]	Xiaoyang Gao, Siqi Chen, Yan Zheng, and Jianye Hao	2021
PS11	Detecting and Learning Against Unknown Opponents for Automated Negotiations [89]	Leling Wu, Siqi Chen, Xiaoyang Gao, Yan Zheng, and Jianye Hao.	2021
PS12	A Bilevel Game Model for Ascertaining Competitive Target Prices for a Buyer in Negotiation with Multiple Suppliers [57]	Akhilesh Kumar, Anjana Gupta, and Aparna Mehra	2021
PS13	A Supervised Topic Model Approach to Learning Effective Styles within Human-Agent Negotiation [90]	Yuyu Xu, David Jeong, Pedro Sequeira, Jonathan Gratch, Javed Aslam, and Stacy Marsella.	2020
PS14	Modeling Opponent Strategy in Multi-Issue Bilateral Automated Negotiation Using Machine Learning [69]	Fatemeh Mohammadi Ashnani, Zahra Movahedi, and Kazim Fouladi.	2020
PS15	Negotiating team formation using deep reinforcement learning [13]	Yoram Bachrach, Richard Everett, Edward Hughes, Angeliki Lazaridou, Joel Z Leibo, Marc Lanctot, Michael Johanson, Wojciech M Czarnecki, and Thore Graepel.	2020
PS16	A hybrid concession mechanism for negotiating software agents in competitive environments [67]	Khalid Mansour	2020
PS17	Agent-based cloud service negotiation architecture using similarity grouping approach [74]	Rajkumar Rajavel, Sathish Kumar Ravichandran, and GR Kanagachidambaresan.	2020
PS18	Deep reinforcement learning for acceptance strategy in bilateral negotiations [75]	Yousef Razeghi, Celal Ozan Berk Yavuz, and Reyhan Aydoğan.	2020
PS19	RLBOA: A Modular Reinforcement Learning Framework for Autonomous Negotiating Agents [17]	Jasper Bakker, Aron Hammond, Daan Bloembergen, and Tim Baarslag.	2019
PS20	Argumentation-based Negotiation with Incomplete Opponent Profiles [29]	Yannis Dimopoulos, Jean-Guy Mailly, and Pavlos Moraitis.	2019
PS21	MCTS-based Automated Negotiation Agent [20]	Cédric LR Buron, Zahia Guessoum, and Sylvain Ductor.	2019
PS22	Numerical Abstract Persuasion Argumentation for Expressing Concurrent Multi-Agent Negotiations [5]	Ryuta Arisaka and Takayuki Ito.	2019
PS23	Meta-Strategy for Multi-Time Negotiation: A Multi-Armed Bandit Approach [47]	Ryohei Kawata and Katsuhide Fujita.	2019
PS24	Automated Negotiation with Gaussian Process-based Utility Models [58]	Haralambie Leahu, Michael Kaisers, and Tim Baarslag.	2019

PS25	Negotiation Strategies for Agents with Ordinal Preferences [30]	Sefi Erlich, Noam Hazon, and Sarit Kraus.	2018
PS26	One-to-Many Multi-agent Negotiation and Coordination Mechanisms to Manage User Satisfaction [70]	Amro Najjar, Yazan Mualla, Kamal Singh, and Gauthier Picard.	2018
PS27	Automated Negotiations Under User Preference Uncertainty: A Linear Programming Approach [84]	Dimitrios Tsimpoukis, Tim Baarslag, Michael Kaisers, and Nikolaos G Paterakis.	2018
PS28	A systematic model of stable multilateral automated negotiation in e-market environment [36]	Taiguang Gao, Min Huang, Qing Wang, Mingqiang Yin, Wai Ki Ching, Loo Hay Lee, and Xingwei Wang.	2018
PS29	A multi-demand negotiation model based on fuzzy rules elicited via psychological experiments [96]	Jieyu Zhan, Xudong Luo, Cong Feng, and Minghua He.	2018
PS30	Emergent Communication through Negotiation [23]	Kris Cao, Angeliki Lazaridou, Marc Lanctot, Joel Z Leibo, Karl Tuyls, and Stephen Clark.	2018
PS31	Concurrent bilateral negotiation for open e-markets: the CONAN strategy [1]	Bedour Alrayes, Özgür Kafalı, and Kostas Stathis.	2018
PS32	The Value of Information in Automated Negotiation: A Decision Model for Eliciting User Preferences [12]	Tim Baarslag and Michael Kaisers.	2017
PS33	POPPONENT: Highly accurate, individually and socially efficient opponent preference model in bilateral multi issue negotiations [95]	Farhad Zafari and Faria Nassiri-Mofakham.	2017
PS34	Designing an intelligent decision support system for effective negotiation pricing: A systematic and learning approach [35]	Xin Fu, Xiao-Jun Zeng, Xin Robert Luo, Di Wang, Di Xu, and Qing-Liang Fan.	2017
PS35	Human–computer negotiation in a three player market setting [40]	Galit Haim, Bo An, Sarit Kraus, et al.	2017
PS36	An Automated Negotiation Agent for Permission Management [8]	Tim Baarslag, Alan Alper, Richard Gomer, Muddasser Alam, Perera Charith, Enrico Gerding, et al.	2017
PS37	Algorithm selection in bilateral negotiation [45]	Litan Ilany and Ya'akov Gal.	2016
PS38	An Agent Architecture for Concurrent Bilateral Negotiations [2]	Bedour Alrayes and Kostas Stathis.	2013
PS39	Complex and Concurrent Negotiations for Multiple Interrelated e-Markets [81]	Kwang Mong Sim.	2012
PS40	Using Gaussian Processes to Optimise Concession in Complex Negotiations against Unknown Opponents [86]	Colin Richard Williams, Valentin Robu, Enrico Harm Gerding, and Nicholas Robert Jennings.	2011
PS41	Automated Negotiation with Decommitment for Dynamic Resource Allocation in Cloud Computing [4]	Bo An, Victor Lesser, David Irwin, and Michael Zink.	2010
PS42	A Multilateral Negotiation Model for Cloud Service Market [93]	Dongjin Yoo and Kwang Mong Sim.	2010
PS43	An Opponent's Negotiation Behavior Model to Facilitate Buyer-seller Negotiations in Supply Chain Management [33]	Fang Fang, Ye Xin, Xia Yun, and Xu Haitao.	2008
PS44	Opponent Modelling in Automated Multi-Issue Negotiation Using Bayesian Learning [44]	Koen Hindriks and Dmytro Tykhonov.	2008
PS45	A fuzzy constraint based model for bilateral, multi-issue negotiations in semi-competitive environments [65]	Xudong Luo, Nicholas R Jennings, Nigel Shadbolt, Hofung Leung, and Jimmy Ho-man Lee	2003
PS46	Optimal Negotiation Strategies for Agents with Incomplete Information [34]	S Shaheen Fatima, Michael Wooldridge, and Nicholas R Jennings.	2001

PS47	On Fuzzy E-Negotiation Agents: Autonomous Negotiation with Incomplete and Imprecise Information [53]	Ryszard Kowalczyk and Van Bui.	2000
PS48 (a)	Strategic Negotiations for Extensive-Form Games [28]	Dave De Jonge and Dongmo Zhang.	2020
PS48 (b)	Automated Negotiations for General Game Playing [27]	Dave De Jonge and Dongmo Zhang.	2017
PS49 (a)	A Deep Reinforcement Learning Approach to Concurrent Bilateral Negotiation [15]	Pallavi Bagga, Nicola Paoletti, Bedour Alrayes, and Kostas Stathis.	2021
PS49 (b)	ANEGMA: an automated negotiation model for e-markets [14]	Pallavi Bagga, Nicola Paoletti, Bedour Alrayes, and Kostas Stathis.	2021
PS50 (a)	Decoupling Negotiating Agents to Explore the Space of Negotiation Strategies [10]	Tim Baarslag, Koen Hindriks, Mark Hendrikx, Alexander Dirkzwager, and Catholijn Jonker.	2014
PS50 (b)	A Tit for Tat Negotiation Strategy for Real-Time Bilateral Negotiations [11]	Tim Baarslag, Koen Hindriks, and Catholijn Jonker.	2013

B List of selected venues for keyword-based search

Table 12: Selected venues with total number of studies

Conference	**No. of studies**	**Journals**	**No. of studies**
Conference on Artificial Intelligence (AAAI)	7539	Foundations and Trends in Machine Learning	23
Adaptive Agents and Multi-Agents Systems (AAMAS)	2320	IEEE Transactions on Pattern Analysis and Machine Intelligence	1449
International Conference on Artificial Intelligence and Statistics (AISTATS)	1622	IEEE Computational Intelligence Magazine	268
International Joint Conference on Automated Reasoning (CADE)	106	Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery	223
Conference on Human Factors in Computing Systems (CHI)	7408	IEEE Transactions on Neural Networks and Learning Systems	2267
Acm Conference on Economics and Computation (EC)	485	Nature Machine Intelligence	410
European Conference on Artificial Intelligence (ECAI)	1546	Artificial Intelligence Review	589
International Conference on Machine Learning (ICML)	4115	Computers in Human Behavior	2600
International Joint Conference on Artificial Intelligence(IJCAI)	4549	Computer Science Review	217
IEEE International Joint Conference on Neural Networks (IJCNN)	4477	International Journal of Intelligent Systems	845
Conference in Uncertainty in Artificial Intelligence (UAI)	660	Neural Networks	1514
IEEE Conference on Systems, Man and Cybernetics (SMC)	3323	Journal of Computer-Mediated Communication	125
ACM Symposium on Applied Computing (ASM SAC)	1511	IEEE Transactions on Emerging Topics in Computational Intelligence	338
International Conference on Advanced Information Systems Engineering (CAISE)	638	ACM Transactions on Intelligent Systems and Technology	350
Conference on Decision and Control (CDC)	4974	IEEE Transactions on Software Engineering	525
IEEE Congress on Evolutionary Computation (CEC)	1892	Decision Support Systems	647
ACM Conference on Computer Supported Cooperative Work (CSCW)	672	Engineering Applications of Artificial Intelligence	1550
Automated Software			

Engineering (ASE)	830	International Journal of Neural Systems	356
ACM SIGSOFT Conference on The Foundations of Software Engineering (ESEC/FSE)	896	Artificial Intelligence	511
Genetic and Evolutionary Computation Conference (GECCO)	2414	Robotics and Autonomous Systems	979
Human-Robot Interaction (HRI)	1467	Journal of Artificial Intelligence and Soft Computing Research	90
International Conference on Software Engineering (ICSE)	1948	Journal of Machine Learning Research	1065
IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)	1002		
Robotics: Science and Systems (RSS)	425		
Total	56819	Total	16941