Integrating neural networks into the agent's decision-making: A Systematic Literature Mapping

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Abstract. *AI systems have been playing a crucial role in many different fields of study. Even though connectionist methods, more precisely deep neural networks, are more prevalent nowadays, many of their limitations have delayed the deployment of AI systems in relevant areas, such as healthcare, financial, and legal. One of its main criticisms relies on the fact that deep neural networks require large data sets, poor generalization, and lack of interpretability. Researchers believe that the next level of AI will require integrating these connectionist methods with different AI's fields. Although many different studies explore this research topic, many of them are surveys or do not cover AI's new advances. A Systematic Literature Mapping is performed to fill this gap, which aims to explore the integration of neural networks into the intelligent agent's decision making. In this study, we analyzed over 1000 papers, and the main findings are: (i) 64% of studies use neural networks to define the learning agent's reward policies; (ii) 5% of studies explore the integration of neural networks as part of the agent's reasoning cycle; and (iii) although 55% of studies main contributions are related to neural networks and agents design, we find that the remaining 45% of the studies use both agents and neural networks to solve or contribute to a particular field of study or application.*

1. Introduction

When decisions derived from intelligent systems ultimately affect humans lives (e.g. medicine, law or legal), there is an emerging need for understanding how AI methods execute these decisions [Goodman and Flaxman 2017, Arrieta et al. 2019]. Even though connectionist techniques are more precise, these methods result in opaque and hard to interpret systems. Since Deep Neural Networks (DNN) now represents the flagship in AI, it is crucial to establish its main limitations. Most of the criticism revolves around data inefficiency, poor generalization, and lack of interpretability [Garnelo and Shanahan 2019a]. In a symbolic approach, we have an easily understandable and transparent system. However, they are known as less efficient [Arrieta et al. 2019, Anjomshoae et al. 2019].

Considering the benefits that both methods bring to AI, many studies have been focusing on combining connectionist and symbolic approaches. The main goal is to increase intelligent systems expressiveness, trust, and efficiency [Arrieta et al. 2019, Bennetot et al. 2019, Garnelo et al. 2016, Marra et al. 2019, Garcez et al. 2019]. The literature presents many works that review the usage of both techniques. Before our study, we find that different parts of [Jedrzejowicz 2011, Garnelo and Shanahan 2019b, Rizk et al. 2018] works are similar to ours, although most of these works are surveys and do not present a systematic review with a well-defined protocol. [Garnelo and Shanahan 2019a] present compelling arguments about the necessity to integrate symbolic and DNN. However, [Garnelo and Shanahan 2019a] do not present a systematic literature review, and its work focus on object representation and compositionality and how they can be accommodated in a deep learning framework. [Rizk et al. 2018] present a survey about how reinforcement learning, dynamic programming, evolutionary computing, and neural networks can be used to design algorithms for MAS decision-making. [Jedrzejowicz 2011] also explores the integration of machine learning and agents. However, we believe that it is required to revisit the last five years of advances in AI.

This step of the research followed the guideline presented in [Kitchenham and Charters 2007] to execute a Systematic Literature Mapping (SLM). We analyzed 1019 papers from Scopus and ACM, and 110 papers remained after applying the inclusion and exclusion criteria. We compiled them to answer the following research questions: (i) which class of agents and neural networks architecture are being employed; (ii) how these studies combine neural network and agents; and (iii) which scenarios are these intelligent systems being deployed.

This paper is organized as follows. Section 2 presents a short review about intelligent agents and Artificial Neural Networks (ANN). Section 3 presents the protocol used to execute this systematic literature mapping. In section 4, we present the main findings of this systematic literature mapping. In section 5 we present the conclusion and future works.

2. Background

In this section will be briefly presented a short review of intelligent agents and ANN.

2.1. Intelligent agents

Despite the existence of different definitions about intelligent agents, in this study, we assume that an agent has specific properties, such as autonomy, social skills, reactive, and proactive [Wooldridge et al. 1995]. Based on these properties, we use [Russell and Norvig 2002] agents classification, which consists of the following types:

- simple reflex agent: performs actions based on the current state of the world, which can map to conditions-actions rules;
- model-based reflex agent: models internal states that can be used during decision-making;
- goal-based agent: defines goals based on a desirable state that it wants to achieve;
- utility-based agent: uses a function that maps a state or a sequence of states to a real number, which defines preferences between different states;
- learning agent: can improve its decision-making by using learning capabilities, which can be improved based on past experiences.

A multi-agent system consists of agents that interact by using a protocol to communicate with each other. Usually, agents represent different people or entities, which each of them could have different goals and motivations [Wooldridge 2009].

2.2. Artificial Neural Network

Neural networks are models inspired by the structure of the brain [Ozaki 2020, McCulloch and Pitts 1990], which provides a mechanism for learning, memorization and generalization. These models can differ not only by their weights and activation function but also in their structures, such as the feed-forward NN that are known for being acyclic, while recurrent NN has cycles [Ozaki 2020]. An ANN consists of different neuron layers, where input layers form the NN, one or more hidden layers, and an output layer [Wang 2003]. Definition 1 is presented in [Kriesel 2007] and models a simple neural network.

Definition 1 *An NN is a sorted triple (N, V, w) with two sets N, V and a function w, where N is the set of neurons and V a set $\{(i, j)|i, j \in \mathbb{N}\}$ whose elements are called connections between neuron i and neuron j. The function $w : V \rightarrow \mathbb{R}$ defines the weights, where $w((i, j))$, the weight of the connection between neuron i and neuron j, is shortened to w_{ij}.*

3. Systematic Literature Mapping protocol

We follow [Kitchenham and Charters 2007] work as a guideline to perform this Systematic Literature Mapping (SLM). An SLM differs from a Systematic Literature Review (SLR) mainly because it presents a broader overview about a field of study, establishes the existence of research evidence, and provides an indication of the number of evidence [Kitchenham and Charters 2007].

According to [Kitchenham and Charters 2007], a systematic literature review or mapping involves several discrete activities. Three main phases with different tasks can divide this process. The phases and tasks that we executed are the following:

- Planning: identification of the need for a review, specifying the research question(s), developing a review protocol, evaluating the review protocol;
- Conducting: identification of research, selection of primary studies, study quality assessment, data extraction, and data synthesis;
- Reporting: formatting the main report and evaluating the report.

3.1. Research questions

In some studies, defining research questions can involve different components and properties. To assist us during this step, we employed the five criteria Population, Intervention, Comparison, Outcomes, and Context (PICOC) presented in [Petticrew and Roberts 2008]. Since our research questions explore the combination of two different approaches, It is worth mentioning that we did not use the comparison criteria of the PICOC method in our study. The main reason for this decision is that our initial research focused on investigating how the integration between agents and neural networks occurs. The PICOC criteria, its definitions, and how it relates with our research are the following:

- P (population or problem): intelligent agents and their different classes;
- I (intervention or interest): which neural networks architecture are employed;
- O (Outcome/results): main contributions achieved by the system originated by combining neural networks and intelligent agents;

- C (Context): scenarios in which the proposed approach was used.

The research questions are defined as follows:

- RQ1: Which class of agents are being used?
- RQ2: Which architectures of neural networks are being used?
- RQ3: How do these works combine neural networks and agents?
- RQ4: Which scenarios are these intelligent systems being deployed?
- RQ5: Do these works contributions focused on improving neural networks, intelligent agents, or both fields?

3.2. Search string

In this work, we decided to use SCOPUS and ACM databases. Since the main goal of this work is to study and analyze the integration between connectionist methods and intelligent agents, the search strings executed in SCOPUS and ACM are the following:

- Scopus: (”deep learning” OR ”neural network”) AND (”intelligent agent” OR ”autonomous agent”);
- ACM: Title:(((”deep learning” OR ”neural network”) AND (”intelligent agent” OR ”autonomous agent”))) OR Abstract:(((”deep learning” OR ”neural network”) AND (”intelligent agent” OR ”autonomous agent”))) OR Keyword:(((”deep learning” OR ”neural network”) AND (”intelligent agent” OR ”autonomous agent”)));

Since it is common to perform an initial search with different strings, we noticed that some works use the term ‘deep learning’ to refer to neural networks during one of these searches. Taking that into consideration, we added this term in our final search string.

Table 1 presents the inclusion and exclusion criteria used to filter the relevant studies in our SLM. As previously mentioned, [Jedrzejowicz 2011] also explores the integration of machine learning and agents development. However, this work did not explore the last five years of advances in AI. Considering that, we believe that it is required to revisit the last five years of AI contributions.

Table 1. Inclusion and exclusion criteria

Inclusion (I)	Exclusion (E)
published between 2015 to 2021	published before 2015
written in English	not written in English
available to download	unavailable to be read
combines neural network and intelligent agent to build an intelligent system	does not use intelligent agents
present a qualitative or quantitative evaluation	does not use the neural network
published in conference or journal	do not present quantitative or qualitative evaluation
primary studies	secondary or tertiary studies

3.3. Selection process

Figure 1 presents the steps performed during the selection, data extraction, and data analyses. Each step contains the number of papers that were selected for the next step. It is important to remark that even after step 4 when inclusion and exclusion criteria were applied, some of the papers did not fit those criteria; therefore, they were removed before the data extraction step. We noticed that some papers were not available to download, which caused a reduction in the number of papers used in the data extraction step. We considered the unavailability of these papers as one of the validity threats. Taking that into consideration, the final number of analyzed papers was 110.

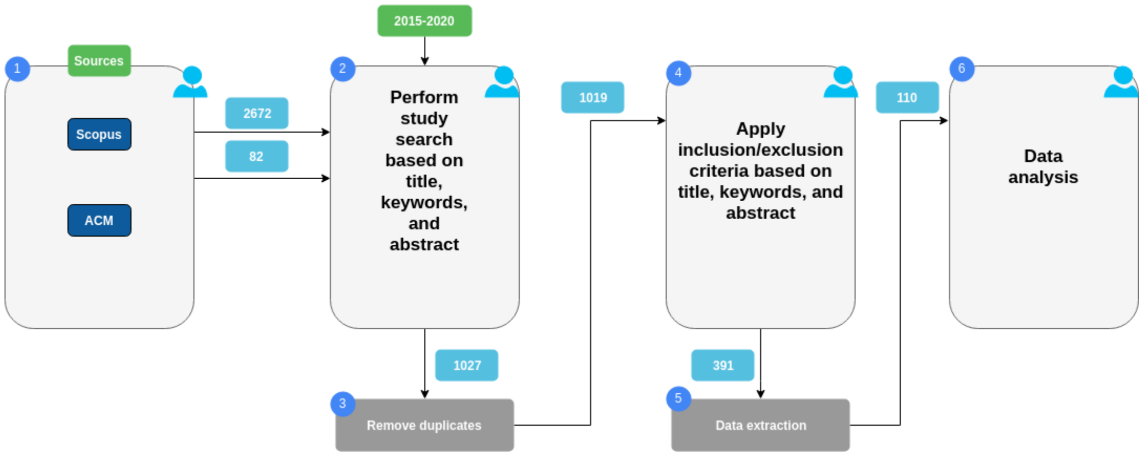

Figure 1. Steps executed during systematic literature mapping.

3.4. Data extraction

The fields and their definitions used during data extraction are the following:

1. RQ1 - Agents class: since an agent terminology and its architectures vary across different works and fields, we chose to use the classification presented in [Russell and Norvig 2002], which defines the following agent's types: (i) simple reflex agents; (ii) model-based reflex agents; (iii) goal-based agents; (iv) utility-based agents; and (v) learning agents.
2. RQ2 - Neural networks types: this field provides information about the type of neural network used;
3. RQ3 - Integration: the primary goal of this field is to study how different works combine neural networks and agents during AI systems development;
4. RQ4 - Contributions: this field identifies what is the main contribution resulted from the combination of neural network and agents;
5. RQ5 - Scenario: this field intends to report where the proposed agent was or intended to be deployed and whether it exists a concern about using these approaches to assist in real-world problems resolution.

   To access the Data extraction form, the reader could click here.

3.5. Validity threats

According to Figure 1, the selection and data extraction were executed by one researcher. This decision is the one that represents more risks to our study and originates the following threats:

1. Researcher expertise: since the steps of studies selection and data extraction were executed only by one researcher that has a background in intelligent agent, some of the relevant features of the neural network could be ignored or wrongfully reported;
2. Data aggregation: based on what is presented in section 4, to answer some research questions were necessary to define groups of agents and the employed neural networks. In this sense, the interpretation of the main findings could present imprecision and limitations;
3. Unavailable papers: we noticed that some papers from relevant conferences and journals were not available to download in our institution, which limited our SLM results.

To mitigate the problems previously presented, we intend to involve two other researchers to revise the data extraction fields. Both researchers are neural network specialists, which enables us to improve the data analyses quality.

4. Results from the data analyses

In this section, we report the most important findings we gathered during the data analyses step. The analyses method and the results employed in our work is called thematic. This method goal is to describe and present an overview of existing works [Dixon-Woods et al. 2006]. The decision to use this approach is supported by the fact that this work is a systematic literature mapping and does not require a qualitative analysis.

We start by showing in subsection 4.1 the retrieved studies distribution. In subsections 4.2, 4.3, and 4.4 we discuss the first three research questions, which are related to intelligent agent's different groups, neural networks architectures, and the combination of neural networks and intelligent agents. Subsection 4.5 presents the main findings of the two remaining research questions.

4.1. Studies distribution between 2015 and 2020

Figure 2 shows the interest in intelligent agents and neural networks in the last five years. The interest in this field starts increasing in 2017, in which the amount of works between 2018 and 2020 represents 59%. It is also worth mentioning that this search occurred on 05/04/2020; therefore, it does not include 2020 in its totality.

4.2. RQ1 - Intelligent agents groups

Figure 3 shows the distribution of different agents returned after the data extraction step. Analyzing Figure 3 it is possible to observe that:

- Reinforcement learning agents usage. Following the results obtained by employing DNN, it is noticeable the usage of reinforcement learning agents. This result could be explained by employing DNN in the definition of reward policies, which represented the main limitation of reinforcement learning. For instance, in [Mnih et al. 2013, Mnih et al. 2015] were achieved relevant results using DNN and reinforcement learning agents.

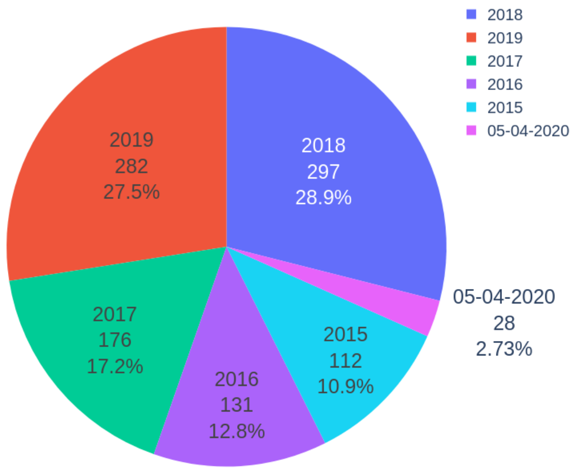

Figure 2. Studies distribution returned from 2015 to 2020.

- Simple-reflex agents. Being one of the most explored types of agents, it is still relevant to point its usage. One of the main reasons is that it is straightforward to combine this type of agent with other techniques since most of the time, the chosen technique acts as decision-making, and the agent only possesses sensors and actuators.

Even though we did not fully explore the Multi-Agent System (MAS) usage, we noticed a relevant increase in combining MAS with reinforcement learning and DNN. This approach points towards a direction where agents could use different policies to coordinate their actions.

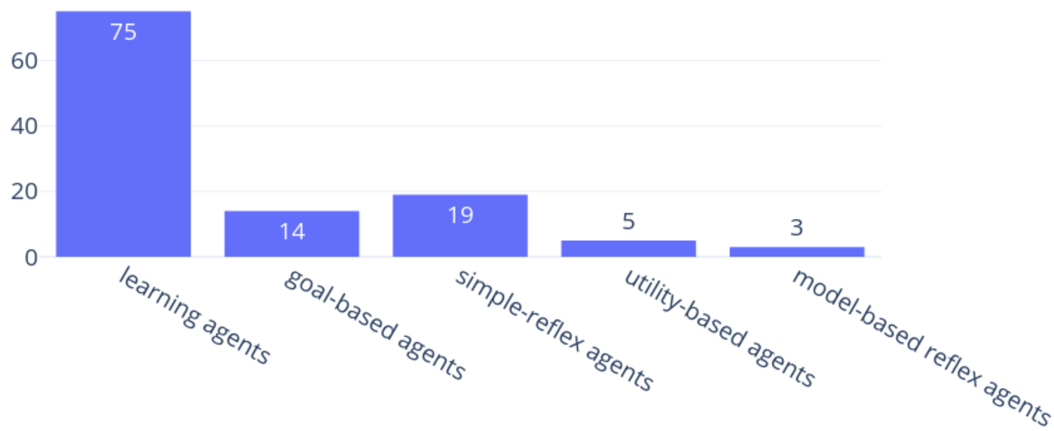

Figure 3. Agents class distribution during the period of 2015 to 2020.

4.3. RQ2 - Neural networks

Following the same approach explored in Figure 3, in Figure 4 we present the most used neural networks architectures during data extraction. Another relevant piece of information is that some works did not accurately report the neural network used. Considering that, we removed the works that did not present information. Since some of the works use more than one type of neural network, the total amount of neural network differs from the number of analyzed papers.

Different from Figure 3, in Figure 4 there is a wider usage of different neural networks. However, convolution, feed-forward, and recurrent neural networks were more frequent. These numbers also agree with the approach used in [Mnih et al. 2013, Mnih et al. 2015], in which these works outperformed all previous approaches on different games and surpass a human expert.

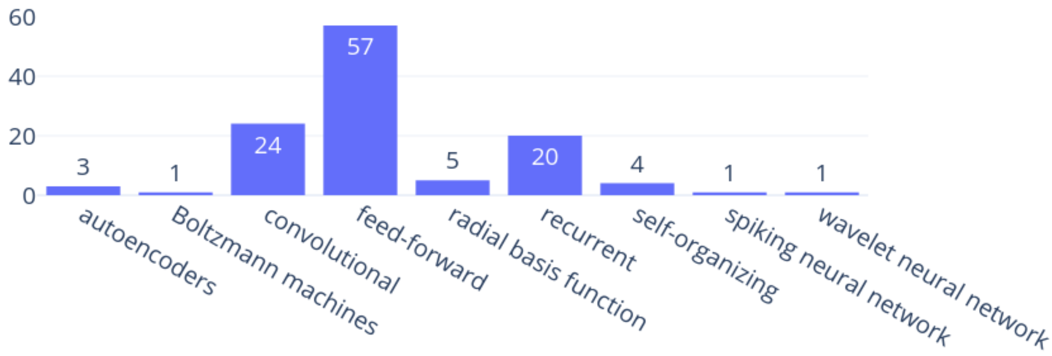

Figure 4. Neural networks architecture distribution during the period of 2015 to 2020.

To answer the remaining research questions, we use a scope analyses approach. A scoping analysis represents a flexible way of providing a broader view of the selected researches, which fits the primary goal of a Systematic Literature Mapping [Dixon-Woods et al. 2006].

4.4. RQ3 - Combination of neural networks and agents

Figure 5 summarizes how studies combine different neural networks architectures and intelligent agents. Two of our study's most relevant findings could be explained through Figure 5. The first one is using feed-forward, convolution, and recurrent neural networks as a mechanism to define reward policies for learning agents, representing 64% of analyzed studies. The second one is that only 5% of studies use the neural networks as an input or combines with the agent's reasoning. This decision could be linked with the implication of combining neural networks in these steps, which requires dealing with many different fields, such as information fusion, knowledge consistency, and planning, for instance.

One of the main reasons for the numbers presented in Figure 5 could be explained by using neural networks to define actions or policies previously explored in the literature and do not require to change the agent's reasoning cycle during decision-making. In this sense, using the neural network as input or part of the decision-making process could require a more robust implementation of these agents.

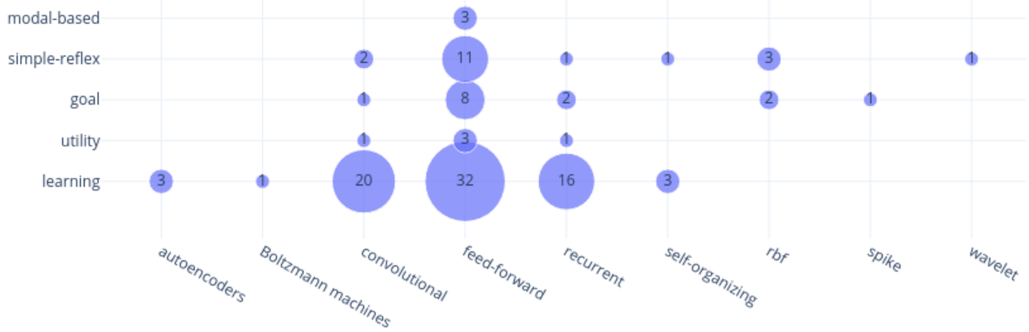

Figure 5. Studies distribution on the usage of different neural networks and intelligent agents.

4.5. RQ4 - Scenarios and RQ5 - Contributions

Even though the spam of contribution from the different works varies, it is possible to define in which group these works focus their contributions. In our study, we define the following group:

- intelligent agents contribution;
- neural networks contribution;
- intelligent agents and neural network contributions;
- application area contribution, in which it was achieved by designing an intelligent system to solve or assist a task resolution in a field of study.

Figure 6 presents the findings related to these contributions groups. Even though 55% of the analyzed studied are contributing to intelligent agents and neural networks design, the remaining 45% represents that combining the existent approaches of NN and agents enables solving problems of different fields of study.

Based on what was obtained during the data extraction phase, the range of scenarios used in the different works varied during this study execution. However, it is possible to define which scenario is more frequent. Many studies contributed by applying agents and neural networks to assist during problem resolution or simulations that model real-world scenarios. It was simulated some behaviour or situation. As presented in [Lamouik et al. 2017, Chen et al. 2019, Loumiotis et al. 2018, Garg et al. 2019, Amrani et al. 2019, Klose and Mester 2019, Kotyan et al. 2019] different studies built systems able to assist humans during task resolution. Some studies showed an agent responsible for driving a car or controlling a traffic light signal autonomously.

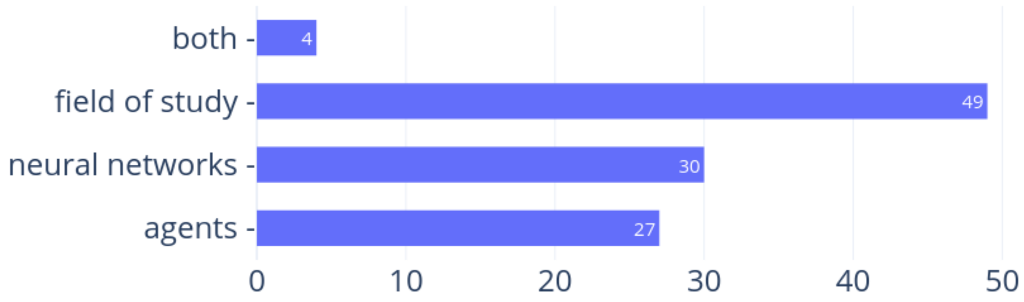

Figure 6. Distribution of contribution between the period of 2015 to 2020.

5. Conclusion and future works

In this paper, we presented a systematic literature mapping, where the main goal was to report an overview of the integration of neural networks into the agent's decision-making. To achieve our goal, we define several research questions related to the type of agents and neural networks employed, which step of the decision-making a neural network was used, the main contributions of these studies, and the scenario in which these systems were deployed. The amount of 1019 papers from 2015 to 2020 shows the relevance of the field explored. The studies from 2018, 2019, and 2020 were responsible for 73,76% of the works used in our systematic literature mapping, showing the field's growth after 2017.

One of the most important findings of our SLM shows that few studies explore the integration of neural networks as part of the agent's decision-making. Most of the studies use neural networks to define learning agents reward policies. Even though these approaches provide significant results, these systems have been suffering from a lack of transparency and require a considerable amount of data [Adadi and Berrada 2018, Arrieta et al. 2019]. This criticism also limits the field of study that an AI system can be deployed, such as in health care, finance, and legal [Garnelo and Shanahan 2019a]. Although many studies contributed to neural networks and agents design, several studies use both agents and neural networks to solve or contribute to a particular study field.

A promising path towards integrating neural networks into the agent's reasoning cycle can be achieved by considering the neural-symbolic field. The neural-symbolic field provides the effective integration of connectionist and symbolic methods, more precisely learning and reasoning [Parisotto et al. 2016]. Neural-symbolic can be employed where large amounts of heterogeneous data exist, and knowledge descriptions are required [Garcez et al. 2015].

As future work, we can explore two different paths: (i) - increase this systematic literature mapping confiability by applying our search string in different digital libraries; (ii) - perform a systematic literature review, using more specific search strings, including multiagent systems and neural-symbolic, and employ quality assessments techniques.

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