# A categorization of BDI integrations: A Systematic Literature Review

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December 2020

## 1 Introduction

The BDI (Belief-Desire-Intention) model is a well known software model for programming intelligent agents. However, this model has some limitations, which can be addressed through the integration of other technologies and techniques. This work aims at categorizing the types of possible integrations to the BDI model, in order to understand in what ways it can be augmented and in which field it can be employed. A Systematic Literature Review process has been carried out following a methodological approach, with the claim of becoming a starting point for defining new research areas and future projects. The work is structured as follows: section 2 describes and documents the research method carried out, section 3 shows the research results divided by category, section 4 summarizes the results in a table, section 5 answers the research questions, finally the conclusions are drawn in section 6.

## 2 Method

A Systematic Literature Review (SLR) is a powerful tool that allows you to collect and summarize the information located in the scientific literature about a specific subject, using a rigorous and reproducible methodology. This SLR was carried out by defining a three-step review process: planning, conducting and reporting.

### 2.1 Research Questions

The research questions that have given rise to the need for this SLR are so defined:

1. How can the BDI model be integrated? (G)
2. Which integration categories are the most widespread? (Q1)
3. Are there technologies to support these integrations or just the models are described? (Q2)
4. Are these technologies effectively used in real-world applications? (Q3)

### 2.2 Source

The search process was conducted on some of the most relevant digital libraries:

- Google Scholar: `https://scholar.google.com`
- IEEE Xplore: `https://ieeexplore.ieee.org/Xplore/home.jsp`

- Springer Link: `https://link.springer.com/`
- ACM Digital Library: `https://dl.acm.org`

The following keywords and their alternatives were defined from the research questions:

- **BDI**: belief-desire-intention, belief desire intention.
- **Integration**: integrat*.
- **AI**: artificial intelligence, artificial-intelligence.
- **ML**: machine learning, learning*.
- **Logic**.

The sources were interrogated using predefined queries, obtained from the previously identified keywords:

- (model* OR technolog* OR technique* OR logic*) AND integrat* AND (BDI OR "belief-desire-intention" OR "belief desire intention") AND (architecture* OR logic* OR model* OR framework*)
- (BDI OR "belief desire intention" OR "belief-desire-intention") AND integrat* AND (AI OR "artificial intelligence" OR "artificial-intelligence" OR "machine learning" OR ML OR learning*)

With the exception of IEEE Xplore which supports fewer wildcards:

- (model* OR technolog* OR technique* OR logic*) AND integrat* AND (BDI OR "belief-desire-intention" OR "belief desire intention") AND (architecture OR logic* OR model* OR framework)

## 2.3 Search Strategy

The documents taken into consideration are those in English and Italian published since 2000. When the search engine allowed it, those with restricted access were filtered.

The amount of articles obtained by submitting the first query to the libraries is abundant. Specifically, 23928 documents were found at the time of the research (Google Scholar = 17200, IEEE Xplore = 69, ACM DL = 770, Springer Link = 5889).

After a brief research conducted on Google Scholar and ACM DL a trend was noticed: after the first 100 results, ordered by relevance, the correlation with the topic decreases. With this in mind, only the first 150[1] results were chosen from each library. These constraints were also used for the second query.

A total of 536 were collected from the first query, 445 for the second, divided as shown in the table 1.

The research was documented by noting each document on an excel sheet, accessible at this location: SLR_Excel_Sheet.

[1] In some cases, fewer results were considered as there was no more correlation with the topic, or the search engine simply found less.

| | Google Scholar | IEEE Xplore | ACM DL | Springer Link | Total |
|---|---|---|---|---|---|
| Query 1 | 150 | 69 | 150 | 167 | 536 |
| Query 2 | 106 | 29 | 150 | 160 | 445 |
| Total | 256 | 98 | 300 | 327 | 981 |

Table 1: Results of the search strategy.

### 2.4 Study Selection

In order to obtain the primary studies from those identified, a filtering process is required. This process is carried out by means of constraints applied in the form of exclusion and inclusion criteria, reducing the body of papers to a selection of the most relevant ones. The criteria that have been applied are defined as follows:

- Inclusion Criteria
  - Full Paper.
  - Sources discussing the topic of this research.
  - Sources answering the research questions.
- Exclusion Criteria
  - Papers not discussing the subject of this SLR: the main check was carried out on the abstract.
  - Papers not answering the research questions: the check is carried out on the full paper.
  - Duplicate reports of the same study.
  - Whole books.

In order to make an efficient selection of the primary studies, the following points have been followed:

1. Duplicates have been searched for and deleted.
2. Titles and abstracts were used as the first filter to check the correlation with the topic to be discussed.
3. The complete papers have been reviewed in detail.

At the end of this selection process, the documents amount to 131. To obtain a more targeted selection, one more check on full paper was performed in the phase of quality assessment, with the result of filtering additional documents, furthermore a final constraint has been added:

4. For each category of integration identified, the documents published since 2010 will be taken into consideration.

   **Specification** In those categories where the number of papers is less than 5, all documents will be taken into consideration, regardless of the date.

5. Finally, one last paper was added to the Primary Studies.

The result can be observed in the table 2.

| Selection Process | | | | | |
|---|---|---|---|---|---|
| **Point** | **Google Scholar** | **IEEE Xplore** | **ACM DL** | **Springer Link** | **Total** |
| 1 | 256-8 = 248 | 98-38 = 60 | 300-113 = 187 | 327-143 = 184 | 981-302 = 679 |
| 2 | 248-138 = 110 | 60-31 = 29 | 187-143 = 44 | 184-125 = 59 | 679-437 = 242 |
| 3 | 110-58 = 52 | 29-6 = 23 | 44-24 = 20 | 59-23 = 36 | 242-111 = 131 |
| 4 | 52-25 = 27 | 23-7 = 16 | 20-10 = 10 | 36-18 = 18 | 131-60 = 71 |
| 5 | / | 16+1 = 17 | / | / | 71+1 = 72 |

Table 2: Results of the study selection.

### 2.5 Quality assessment

As anticipated in the study selection phase, the quality assessment was carried out as step four of the table 2. From the 131 remaining papers, the content was checked in detail and some documents were removed. Moreover, with the addition of the constraint of the publication date, a further quantity of documents has been filtered. After one final paper has been added to the collection, the amount of primary studies (PMs) is 72. The full process is detailed on the tables of this excel sheet: SLR_Excel_Sheet.

## 3 Results

The results of this SLR are illustrated in this section. To provide a clear view, the section is divided according to the macro categories of integration that have been identified. Furthermore, the studies were sorted according to the date of publication.

### 3.1 Decision Making

The focus of this category is to manage the way agents make decision. The following papers present different decision making approaches integrated to the BDI model.

- In [65] is proposed a way of integrating a recognition-primed decision making approach with the BDI agent architecture. The purpose of this work is to obtain a more naturalistic way of tackling the problem of which plan should be chosen when there are multiple applicable plans. The reference model is Klein's recognition-primed decision making (RPD) model [49], a model focused on situation assessment.

- The article [52] introduces a model for integrating internal performance measures into the decision making process. A model inspired by concepts of psychoanalytical meta psychology is introduced and it is proven that it can be realized and used within the decision unit of an agent. The main concept of this model is the drive, the first psychic representative of the demands of the bodily organs and signals a bodily need. The desires defining the agents goals are complemented with a new sort of desires: internal desires. A description of the complete model can be found in [31], this paper focuses only on a specific part of it.

- In [90] an abstract framework which incorporates agreement technologies in decision processes within BDI agents is presented. The BDI architecture incorporates an Inner Decision Making Component (IDMC) which makes inner decisions with respect to the different alternatives and the multiple criteria provided to the agent. A voting-based instantiation of this framework is also proposed.

- The article [46] presents the implementation and the integration of coherence-driven adaptive decision making DeCoAgent architecture into a concrete BDI architecture. DeCoAgent is a cyclic repetition of the phases: intelligence, design, choice and implementation. A connectionist model, a graph of relations among the goals and tasks, provides the ability of creating dynamic relationship between goals and tasks, while handling multilateral positive relationships. It enables an adaptive goal deliberation mechanism.

  **Technology** A Jadex extension provided as a Java package is implemented.

  This work has an homepage with the reference to the package at `https://sites.google.com/site/okantopcu/decoagent`.

  Jadex can be found at `https://github.com/actoron/jadex` under GPL-3.0 license.

### 3.2 Emotions

One of the shortcomings of the BDI model is that it does not take into account the agent's emotional mental states in its process of decision making [40]. For this reason the following works aim to fill this lack.

- The work in [72] combines the Emotional BDI agents framework with the principles of empathy in psychology and neuroscience, to provide a powerful tool for the building of robust agent teams, resilient to faults and unforeseen changes in the environment. The idea is to use empathy as a mechanism for deciding how to choose among the plurality of options in offering support to others who need it. Affective and behavioral responses are defined in a hierarchy and integrated into an algorithm that formalizes the interactions between the subject and object of empathy: the Empathic Behavioral Response Algorithm (EBRA). The model of empathy is patterned after the Perception-Action Model (PAM). The pseudo-code of the algorithm is presented and the concept of the EBDI architecture are introduced in the work in [48].

- In [10] an emotional agent model integrates a computational model of emotions, with the aim of building agents with believable and realistic behaviors. The process of emotion generation is based on a psychological model of emotions named the OCC model. The agent conduct can be summarized in 3 step: perception, appraisal, behavior. The beliefs of an agent are appraised in order to generate the emotional state and the intentions are induced by the emotional state and the desires. Given the active goal, the suitable sequence of actions is selected to be executed.

  **Technology** A part of the proposed model was implemented into the civilian agents of the RoboCupRescue (RCR) simulation system but there are no references to the implementation.

  `https://rescuesim.robocup.org/`.

- The work in [40] allows to differentiate between emotions and affective reactions: the emotion intensity determines the intensity of the reaction, in particular of event-based emotions with consequences for self. The emotions are based on the OCC cognitive psychological theory of emotions. The implementation of the emotions and their intensity is defined using a language that integrates BDI logic and probabilistic Bayesian Reasoning. Bayesian Networks (BN) extended with utility and decision nodes, are exploited to model the agent's behaviour using Decision Theory. These extended BN are called Bayesian Decision Networks (BDN).

**Technology** AgentSpeak(PL) has been used to implement the probabilistic process of appraisal of the emotions. AgentSpeak(PL) is a is a new agent-oriented language that integrates the concept of probabilistic beliefs through the use of Bayesian Networks, to core BDI programming concepts [79].

- In [87] a work on the influence of student's emotional engagement onto their education is presented. A conceptual emotion based model is animated by an agent-based social simulator. An E-BDI architecture is introduced, with an emotional component representing the emotions experienced by an agent, who plays the role of a lecturer, towards the student's engagement.

- In [15] is presented a cognitive agent architecture coupled with an emotional engine, with the aim to propose to modelers a tool to create emotional agents. The emotion module is based on the OCC theory.

**Technology** The architecture is implemented in GAMA, a multi-agent software for modeling and simulating complex systems. The work consists in upgrading the existing cognitive architecture previously developed in [19] and in integrating an engine that simulate emotions.

Examples on how the developed tools can be used are accessible at `https://github.com/mathieuBourgais/ExampleModels`.

Gama can be found at `http://gama-platform.org` and on `https://github.com/gama-platform/gama` under GPL-3.0 License.

### 3.3 Intention Selection

The mechanisms for intention selection generally supported by typical BDI infrastructures are very simplistic. Most existing BDI platforms only provide rudimentary intention scheduling mechanisms such as First-In-First-Out (FIFO), Round Robin (RR), or simple priority-based schedulers [94].

For this reason, the following works describe new approaches to this topic.

- The study in [12] proposes AgentSpeak(XL), an extension to AgentSpeak(L) for improving that language in various aspects and in particular to accomodate the on-the-fly use of a decision-theoretic task scheduler in order to automatically generate efficient intention selection functions. The work in this paper uses TÆMS as a representation language [30] and also the Design-to-Criteria Scheduler (DTC) [92].

- In [94] two domain independent intention selection mechanisms based on the ideas of enablement checking and low coverage prioritisation are implemented and evaluated. In particular three new intention selection mechanisms are implemented:
  - Enablement checking is the idea of determining whether or not an intention's next step will be to post a sub-goal with no applicable plans in the current state. Two of the three mechanisms add this idea to the existing mechanisms of FIFO and RR.
  - Low-coverage prioritisation is based on the intuition that if a given intention is "vulnerable", in that it can only successfully execute in a limited set of world states, then it should be prioritised for execution when an opportunity arises. The last mechanism implements this approach.

**Technology** These intention selection mechanisms have been implemented in Jack but there are no references to the implementation.

`http://www.agent-software.com.au/products/jack/`.

- From the same author of [94] a similar work is presented in [93], where a proposal for domain-independent intention selection using the notion of plan "coverage" is implemented and evaluated.

## 3.4 Logic

In this part, some works related to logic are introduced.

- In [68] an integrated framework, based on Propositional Dynamic Logic and Belief and Intention modalities, and a PDL-BDI language, with multi-modal logic, are presented. An axiomatisation of the aforementioned language is provided to represent and reason about the semantics of Agent Communication Languages (ACLs) and Interaction Protocols (IPs). Moreover, axioms for expressing both an agent's social attitudes and its belief about the exchange of messages are formulated.

- The paper [85] describes the development of an agent-based simulation model used to analyze and evaluate the governance of the Brazilian Financial System. The modeling success should be credited to the use of fuzzy logic in representing the behavior of the agents within the BDI architecture. In particular, a fuzzy-extension of a BDI agent model where the specification and description of the agents behavior are carried out by means of fuzzy rules, is proposed.

  **Technology** The implementation of the model was developed in the Jason Framework. For the development of the Java classes that define the actions by means of fuzzy logic, a library of classes called FuzzyJ (NRC FuzzyJ Toolkit) was used.

  The Open Source version of the toolkit is released under the Mozilla Public Licence 2.0 and can be found at `https://github.com/rorchard/FuzzyJ`.

  Jason is available at `https://github.com/jason-lang/jason` under the LGPL-3.0 License and continuous to be updated.

- A multi-agent systems formed by the modal logic framework DEAL (deontic epistemic action logic) and the BDI model is discussed in [96]. This work relate the knowledge about what is morally acceptable, and what is not, to the desires of the agents and the formation of its intentions. The purpose of this work is to constrain the behavior of the agents to make them more acceptable to their human counterparts. The Deontic logic is also called the logic of obligations.

- In [71] the Repage model [76] is integrated in a BDI agent. The aim of this work is to define the belief logic that the BDI architecture uses to perform logical reasoning over beliefs that model social evaluations coming from Repage, and beliefs that model the general knowledge that the agent has gathered. This logic can deal with several independent probabilistic distributions. A first-order many-sorted language called $\mathrm{L}_{\mathrm{bc}}$ is used to capture the knowledge of an agent at a given instant of time. In particular, $\mathrm{L}_{\mathrm{bc}}$ can translate the image and reputation predicates from Repage into probabilistic formulas, and transform such information into beliefs.

- In [22] Coalition logic (CL) enables the modeling of strategic abilities and gives the ability to specify what a group of agents can achieve whatever other agents do. This first-order coalition BDI (FCBDI) logic for multi-agent systems, provides a semantic glue that combines BDI, coalition and temporal operators in a single first-order-language. The BDI logic used in this paper is the observation-based BDI logic discussed in [86], where a concrete algorithm is successfully proposed and implemented. The final FCBDI logic, is a multi-modal logic.

## 3.5 Machine Learning

The BDI model lacks learning techniques, which is why the following works try to integrate them to improve the capabilities of the model.

- In [89] the integration of reinforcement learning (RL) techniques is proposed to enhance the agent planning. Based on the goals defined in the desire module and the sensory inputs received from the environment, RL is performed to acquire a set of action and value policies that enables the agent to achieve its goals. The degree of goal attainment can then be used as an implicit reward signal.

  **Technology** This hybrid architecture integrates BDI features with a RL system, the Temporal Difference-Fusion Architecture for Learning and COgNition (TD-FALCON). TD-FALCON is also an extension of a class of self-organizing neural networks, the Adaptive Resonance Theory (ART).

  The sample codes and test can be found at `https://github.com/chen0040/java-adaptive-resonance-theory` with a MIT license.

- In [83] a framework for improving plan selection of BDI agent through adaptive machine learning techniques is presented. The plan's applicability condition is determined by learning the structure of a decision tree and the learnt structure will summarise the set of experiences and classify them. The goal is to be able to decide likely outcome in unseen situations. Moreover, a dynamic confidence measure that adapts accordingly with changes in performance, is employed to define practical heuristic for guiding exploration.

- In [3] the use of Reinforcement Learning is adopted in a test generation scenario, in order to increase the effectiveness of the BDI verification agents by exploiting coverage feedback loop that systematically explores the BDI agents.

  **Technology** The data on the simulator, test generation methods and results are available at `https://github.com/robosafe` under GPL-3.0 License.

- In [4] an experimental interactive application that incorporates Reinforcement Learning agents is developed. The system incorporates Jason agents that use basic algorithms for passive Temporal Difference Learning (TDL) as well as active Q-learning and SARSA.

  **Technology** The system is built on the Jason implementation based on the Java platform of AgentSpeak(L). There are no references to any implementation nor repositories of this project.

  Jason is available at `https://github.com/jason-lang/jason` under the LGPL-3.0 License and continuous to be updated.

- In [33] a library of learning algorithms is included in a BDI model to cater to adaptability. After a desire is chosen, learning algorithms are used to deliberate and arrive at an intention of which desire option to continue. Two kinds of algorithms have been implemented: Temporal Difference (TD) learning and Q-learning.

  **Technology** Two case studies have been implemented in Netlogo, an open source tool to model the design of multi-agent systems. There are no references to any implementation nor repositories of this project.

  Netlogo can be found at `https://github.com/NetLogo/NetLogo` under GPL license.

- In [64] is presented an integration of machine learning with BDI agent, with the purpose of devising a BDI architectures where agent's reasoning is enhanced with cognitive computing. A Long short-term memory (LSTM) is adopted, the most effective sequence models among Recurrent Neural Networks (RNNs). The system is a continuous interaction between a Trauma Assistant Agent and a service called Trauma Cognitive Service.

  **Technology** From the related work in [24], it follows that the Trauma Assistant Agent is developed using the JaCaMo platform, which integrates Jason with the CArtAgO platform. In particular a version of JaCaMo for mobile and wearable devices: JaCa-Android. There are no references to any implementation nor repositories of this project.

  These technologies can be found at `http://jacamo.sourceforge.net/` and on github `https://github.com/pslabunibo/jaca-android` under GPL-3.0 License

## 3.6 Model

This section deals with the integration of different kind of models to the BDI one.

- In [14] the development of a BDI-model that generates culturally consistent behavior is presented. This architecture integrates the Culturally Affected Behavior language (CAB) [84] with modeling behavior as a function of Beliefs, Desires and Intents. The CAB-BDI model was also extended with a Five Factor Model (FFM) [32], a descriptive model which describes a personality using five dimensions. A central concept of the work is the agent's Socio Cultural Satisfaction (SCS), a value representing the agent's appraisal of the current interaction. It is used to calculate intention probability, which in turn is used for plan deliberation.

  **Technology** The architecture was implemented in Jadex. There are no references to an implementation of this project.

  Jadex can be found at `https://github.com/actoron/jadex` under GPL-3.0 license.

- Inspired on natural selective attention studies, a computational model of selective attention is presented in [60] and supported in its argument [61]. This model relies on the assumption that uncertain, surprising and motive congruent/incongruent information demands attention from an intelligent agent. The integration into the architecture of a BDI artificial agent allows the agent to autonomously select relevant, interesting information of the environment while ignoring less relevant ones.

- The paper [99] integrates the BDI model and Petri net modeling methods, representing beliefs and desires by places, intentions by transitions with bottom subnet and the dynamic process by the flowing colored tokens among different places. The most promising application of the BDI Petri net is on the modeling behaviors of unmanned aerial vehicle (UAV) and multi-agent cooperation.

- [63] introduces a new framework for the implementation of the BDI model for the development of an agent based decision support system for the control of public transportation systems. This framework is inspired by concepts of biological immunity, in particular, on immune memory and on the mechanism of affinity. A parallelism is made between Biological Immune Systems (BIS) and Public Transportation Control Systems (PTCS) and a matching between BDI concepts and developed immune features is created.

- In [17] an hybrid framework that combines diffusion modelling with cognitive agent modelling is proposed. Diffusion models are powerful tools for understanding the spread of diverse content such as information, opinions, rumours and ideas through social networks. The diffusion model is generalised in two functions:

  – An influence aggregation function that quantifies the aggregate influence received from a social network, used to update the network influence belief in the BDI model.

  – A decision function that determines the response behaviour to the received network influences in terms of a social state or an influence level.

  This model also supports non progressive diffusion modelling: an influence level can either increase or decrease as the effects of dynamic events are incorporated into the diffusion process.

  **Technology** A github repository containing an experiments of diffusion-evacuation have been found after some research.

  `https://github.com/chambul/diffusion-evacuation-experiments` under LGPL-3.0 License.

- In [88] the application of a well-known psycho therapeutic model, the Ellis's ABC theory [34], to the modeling of intelligent agents is proposed, obtaining a framework called ABC-EBDI. It is an emotional BDI (EBDI) whose affective component considers emotions, mood, personality and influences the cognitive processing. The distinguishing feature is the classification of the agent's cognitive-affective process as either rational or irrational.

  **Technology** To simulate the BDI agent processing, the Jadex tool has been chosen.

  Jadex can be found at `https://github.com/actoron/jadex` under GPL-3.0 license.

## 3.7 Planning

To achieve the full potential of the BDI architecture, it is necessary to specify an adequate plan selection algorithm [35]. Different approaches to plan selection are proposed in the following works to address the current planning limitations.

- [82] addresses the planning limitations of the BDI model by proposing a novel BDI programming framework that, by suitably modeling context condition as decision trees, allows agents to learn the probability of success for plans based on previous execution experiences. A probabilistic plan selection function is defined to balance the exploration and exploitation of the agent's plans. Each plan of the agent's library is associated with a decision tree that classifies world states into an expectation of whether the plan will succeed or fail. Plans are then selected with a probability proportional to their expected success. Two learning approaches are considered: the aggressive concurrent learning (ACL) and the bottom-up learning (BUL). An extended version of this work is introduced in [81], where both parameterised goals and recursion are included.

  **Technology** The learning agent system was implemented in the JACK BDI platform and the empirical evaluation of the second work was shown on an example program developed for the JACK tutorial by Agent Oriented Software.

  `http://www.agent-software.com.au/products/jack/`

- In [29] a multi-agent system that incorporates agents with automatic planning capabilities based on CBP-BDI (Case Based Planning) architecture is presented. In [28] an Intelligent Biomedic Organizations (IBOs) model is based on that architecture. The agents act as Web services coordinators that implement the four stages of the case-based planning cycle. The Bayesian networks make it possible to generate the plans that best adjust to the different case studies, allowing the generation of new plans based on existing information without actually needing an existing memory of plans.

  **Technology** The system has been implemented in a real scenario to classify leukemia patients but there are no references to the implementation.

- The paper [67] addresses the issue of dynamically assigning a value to a plan instance by describing an extension for AgentSpeak like languages, that provides a declarative mechanism for capturing priorities or preferences that are based on the specific situation, and/or the specifics of the plan instance. The framework uses specifications based on logical formulae which are evaluated dynamically. The approach is to assign a quantitative value to each plan instance using local preference specification.

  **Technology** A basic implementation of the proposed extension was developed as an add-on Java library for use with the JADEX agent programming platform. This extension is available for download with instructions and a working example.

  `https://sites.google.com/site/rmitagents/software`

  `https://github.com/actoron/jadex` under GPL-3.0 license.

- In [77] the application of Genetic Algorithms (GAs) as a mechanism for re-planning in BDI agents is explored. The main idea is that if a BDI agent finds itself in a changing environment, where it is fairly easy to devise new plans, but time consuming to find optimal solutions, it may well be feasible to use GAs to develop new plans. A Genetic Algorithm Plan Optimizer (GAPO) is defined to develop and optimize new plans when those in the plan library start failing.

  **Technology** The agents are built using the Java Jadex library. The GAPO was implemented in jgap.

  `https://github.com/actoron/jadex` under GPL-3.0 license.

  `https://sourceforge.net/projects/jgap/` under GNU Library or Lesser General Public license version 2.0 (LGPLv2), Mozilla Public License 1.1 (MPL 1.1).

- In [59] intentional learning is developed within the Jason BDI framework, with focus on a plan acquisition strategy addressing the cases of learning plans composed of: one action, sequences or a repetition of actions. The feasibility of including learning driven by intentions and manipulative abduction in a pure BDI agent environment is exhibited in a pure BDI agent environment. Moreover, the use of Reinforcement Learning techniques for action selection confers the agent the capability of learning through interacting with the environment.

  **Technology** Jason is available at `https://github.com/jason-lang/jason` under the LGPL-3.0 License and continuous to be updated.

- In [35] it is proposed a plan selection approach, which is able to learn plans that provide possibly best outcomes, based on a current context and agent's preferences. The approach is composed of two part:

  – A metamodel to be instantiated to specify plan metadata.
  – A technique that uses such metadata to learn and predict plan outcomes.

  The aim is to build a prediction model based on recorded plan executions. For this reason an initial learning stage is needed to collect a minimal amount of data and extract useful information. Existing machine learning algorithms are exploited to predict outcome values given the collected data: any algorithm able to perform regression can be used in this approach. In this case the linear regression algorithm was chosen. The work in [36] details an empirical evaluation of this architecture to address the Braess' paradox.

  **Technology** The meta-model is implemented as an extension of the BDI4JADE platform but there are no references to the implementation.

  `https://www.inf.ufrgs.br/prosoft/bdi4jade/` under GNU Library or Lesser General Public License version 2.0 (LGPLv2).

- In [98] a novel operational semantics for incorporating First-Principles Planning (FPP) as an intrinsic planning capability to achieve goals in BDI agent systems is proposed. A declarative goal intention is introduced to keep track of declarative goals used by FPP and develop a detailed specification of the operational behaviour when FPP is: pursued, succeeded or failed, suspended or resumed. The framework Can(FPP) is the result of an extension of the Can language [97]. This framework allows to define agents that can perform FPP. The purpose of this work was not to present a fully developed Can(FPP) system but to motivate the merits of the proposed framework.

  **Technology** An offline first-principles planner called Fast-Forward planner was chosen and the Planning Domain Definition Language (PDDL) [39] was employed for specifying planning problems for the first-principles planner in a concrete example.

  `https://fai.cs.uni-saarland.de/hoffmann/ff.html` under the GNU General Public License.

### 3.8 Probabilistic

It is believed that a probabilistic reasoning capability is a vital part of any system that attempts to emulate human intelligence computationally [27]. The next works aim to fill this need by integrating probabilistic reasoning into the BDI model.

- In [58] is proposed a mechanism of relevance-based belief update implemented in a BDI cognitive agent. At an architectural level, a Bayesian network has been realized to govern goal deliberation and intention selection.

  **Technology** The experimental platform has been built on top of CArtAgO, a Java-based framework for programming environments in agent-oriented applications. The agents have been implemented by extending Jason.

  `http://cartago.sourceforge.net/` under the GPL-3.0 License.

  `https://github.com/jason-lang/jason` under the LGPL-3.0 License and continuous to be updated.

- In [54] a BDI modeling framework is integrated with submodules based on a Bayesian Belief Network (BBN), Decision-Field-Theory (DFT) and a Probabilistic Depth-First Search (PDFS) technique. This way the agents decision making process is enhanced: the planning is performed via PDFS, which in turn accesses DFT and the BBN, obtaining preferences and assessing the environment.

**Technology** The BDI architecture is an extension of the one described in [100]. The simulated environment and agents are implemented in AnyLogic 6.0 agent-based simulation software. Moreover, Netica has been used for BBN, JAMA for DFT and Soar for PDFS.

`https://www.anylogic.com/`.

`https://www.norsys.com/index.html`

`https://math.nist.gov/javanumerics/jama/`

`https://soar.eecs.umich.edu/`.

- In [79] a new agent oriented programming language, AgentSpeak(PL), is presented. AgentSpeak(PL) is based on AgentSpeak(L), a classical BDI programming language. This language integrates the concept of probabilistic beliefs through the use of Bayesian Networks, to core BDI programming concepts.

  **Technology** This work follows the guidelines of AgentSpeak(L) and defines the operational semantics of AgentSpeak(PL). In addition, a programming tool is also created: the JasonBayes agent programming environment, developed in Java as an extension of the Jason agent development environment.

  `https://github.com/jason-lang/jason` under the LGPL-3.0 License and continuous to be updated.

- In [27] a cognitive architecture used to govern a robot probabilistically is presented. This project is called Cerno, and is an extension of the CAMAL (Computational Architectures for Motivation, Affect, and Learning) model [26]. The purpose of the project is to incorporate probabilistic reasoning (bayesian theories) in the BDI model of CAMAL. The belief statement are represented as graded states using an Extended Belief Structure (EBS) and a numerical reasoning algorithms associates a probability value in every belief statement.

- Probabilistic Graphical Models (PGMs) are incorporated into a BDI architecture in [23]. In particular, the PGMs are Bayesian Networks (BN) and influence diagrams (IDs) included in the agents' epistemic state and used to model the uncertainty reasoning and decision making process of agents in a stochastic environment. This integration makes use of BN to reason about the agent's beliefs and selects the optimal plans according to the utilities action defined in influence diagrams.

  **Technology** AgentSpeak was chosen as the agent-oriented programming language and the scenario was implemented using Jason. Hugin [2] to reason over the embedded PGMs.

  `https://www.hugin.com/`.

  `https://github.com/jason-lang/jason` under the LGPL-3.0 License and continuous to be updated.

- In [74] to capitalize on their complementary strengths, an agent architecture which combines Partially observable Markov decision processes (POMDPS) and the BDI framework is proposed. In this hybrid POMDP-BDI architecture, an agent can concurrently perform rewarding actions, not directly related to its goals, while pursuing goals. This is useful in dynamic stochastic environments, where multiple goals and goal types must be pursued. A notion of intensity of the desire for a goal's achievement and an update rule for the desire level are introduced.

- The AgentSpeak+ framework is proposed in [6], with an approach similar to [74]. This framework is an extension of AgentSpeak with a mechanism for probabilistic planning: Partially Observable Markov Decision Processes (POMDPs). Epistemic states are used to represent the belief of the agents, allowing it to reason about its uncertain observations and uncertain effects of its action. Each state consists of a POMDP, used to encode the agent's knowledge of the environment, and its associated probability distribution.

**Technology** A prototype implementation of the framework has been developed by extending Jason with Hugin [2], a proprietary tool for constructing and evaluating Bayesian networks. The prototype suffers from its overall complexity.

`https://github.com/jason-lang/jason` under the LGPL-3.0 License and continuous to be updated.

`https://www.hugin.com/`.

## 3.9 Reasoning

Works talking about improving the reasoning abilities of agents are discussed in this section.

- In [5] is demonstrated how to derive an event-based run-time model of institutions that can be incorporated into the reasoning processes of autonomous BDI agents to realize practical norm-governed multi-agent systems. The work is divided in two parts:
  - Normative and system perspectives are expressed as a logic program under answer set semantics (ASP) [38] to define a design-time model.
  - A run-time model is extracted from the design-time model, by removing all but the normative information and domain facts.

  The run-time model provides the agents with an oracle that can respond to queries both about the current state and the normative consequences of actions. To use the run-time model in a live system, it needs to be encapsulated in a monitor object, in this work called Governor, whose sole purpose is to manage normative states and to answer queries from norm-aware agents.

  **Technology** The run-time reasoning was implemented using the Jason platform, linked to the institutional model and answer set solver using system calls.

  `https://github.com/jason-lang/jason` under the LGPL-3.0 License and continuous to be updated.

- The first step in allowing an agent to reason about its trust model, by providing a method for incorporating a computational trust model into the cognitive architecture of the agent, is proposed in [50]. A complete formalization of this method is given by incorporating the trust model into a multi-context system (MCS) representing the BDI framework, and a general method that can be applied to particular trust models is illustrated. First-order dynamic logic (FODL) was used, referring to the formal semantics defined in [43]. A logic called Priority Logic, a subset of first-order logic, is also required to formalize a structure of priorities between predicates in the MCS. The demonstration is done by incorporating three different trust models: BRS [45], ForTrust [57] and ReGReT [62].

- In [47] the AORTA (Adding Organizational Reasoning to Agents) architecture for making agents organization-aware is described. It is designed to provide organizational reasoning capabilities to agents implemented in existing programming languages without being tied to a specific organization model. The architecture of the agent is independent from the organization model, and the agent is free to decide how to use AORTA in its reasoning. Concepts of Organizational Theory (OT) have been used. AORTA puts the organizational reasoning into a separated component inside the agent, connected to its mental state. In this work an AORTA project in Jason is presented to demonstrate the possibility to create one without having to deal with the specifics of the integration.

**Technology** AORTA makes use of tuProlog, so the contents of the agent's knowledge bases should be translated into Java objects supported by tuProlog. AORTA has a main site and the open source code is available on github.

`http://www2.compute.dtu.dk/~ascje/AORTA/`

`https://github.com/andreasschmidtjensen/aorta`

- In [37] is proposed a model definition in which trust processes are part of the agents' reasoning cycle, influencing and being influenced by the emotions of the agent. The agent model is introduced as a Multi-context system (MCS), where beliefs, desires and intentions as well as communication interface are contexts. Trust and reputation are integrated into the aforementioned agent. To represent emotions, a formalization of the OCC model following the work in [11] has been used, as for the trust model, this work was focused in the numerical trust model ReGreT [62].
- In [95] a method of integrating case-based reasoning (CBR) into BDI Agent is proposed to create an active guidance model of university network public opinion. CBR tries to mimic the people tendency to solve new problems by finding a similar historical cases and using specific knowledge of existing experience or results. Two methods are discussed:
  - Method 1: CBR technology is used as the inference engine of BDI agent to perfect the inference process.
  - Method 2: The 4R steps (case retrieval, case reuse, case revision and case retention) of case inference, are implemented by the specified BDI agent respectively.

  **Technology** The implementation of the model was done in the Jadex platform.

  `https://github.com/actoron/jadex` under GPL-3.0 license.
- The purpose of the work in [53] is to reproduce the human ability to cooperate and collaborate in a dynamic environment, in particular the ability to make run-time planning with not known factors. A Non-Axiomatic Reasoning System (NARS) is embedded into the internal structure of the Jason agent by using an extended Internal Action, without changing the basic reasoning cycles.

  **Technology** Jason is available at `https://github.com/jason-lang/jason` under the LGPL-3.0 License and continuous to be updated.

  The open-source version of NARS can be found on github `https://github.com/opennars/opennars` under the MIT License.

## 3.10 Semantic Web

One of the possible integrations that has been identified aims to increase the knowledge available to agents by means of semantic web ontologies.

Some articles discussing this topic are presented:

- In [44] the OWL ontologies are employed as a knowledge base for intelligent software agents that operate in the environment. The agents use these facts to populate the agent's world model and operate on these facts. The ontology is represented in RDF/XML, a knowledge representation language that allows information to be described as a set of factual sentences.

  **Technology** The agents are developed in the JACK Agent Language and a semantic web framework called Ilium Framework is proposed. Finally, a SPARQL library is presented to allow the agents to make direct queries to the ontology.

  `https://www.w3.org/TR/rdf-sparql-query/`.

  `http://www.agent-software.com.au/products/jack/`.

- In [55] the agent technology is integrated with semantics to develop a solution to Web service composition. The result is an automatic service composition framework in which agents can exploit the OWL-S description to search for specific web servers that meet the user requests.

- To enhance agents capabilities with the ability to reason about the Semantic Web content, goal models should be integrated with languages of the Semantic Web. For this purpose, in [42] a Description Logic (DL) based goal model is proposed and a BDI architecture built on top of DL components is introduced. In this approach the goal management is based on DL transition rules, constructed from conceptual goals.

- In [41] an integration between the Rule Interchange Format (RIF) and BDI is expected to enhance the reasoning capability of the agents by using existing resources in RIF compatible technologies. It is expected that the rules in RIF format can be translated into executable rules for BDI agents and vice versa. The choice of RIF derives from the fact that other technologies of the semantic web are compatible with it, such as OWL and RDF, becoming a language that acts as an intermediary between semantic web languages and bdi languages. The AgentSpeak language is employed to present BDI and the RIF rules are translated into it.

- In [56] agent can proactively interpret the static OWL-S description. An ontology-based BDI agent architecture is proposed, in which a BDI agent proactively binds web services according to a customized workflow that is dynamically generated to meet a user request.

  **Technology** The architecture is based on the Jadex platform.

  `https://github.com/actoron/jadex` under GPL-3.0 license.

- In [20] an integration of ontology and agent systems is proposed as a solution for searching diverse barter database and to resolve common barter problems. The semantic approach used for the bartering matching consist in using the semantic proximity metric.

  **Technology** The multi-agent system has been implemented using the JACK intelligent Agents framework The ontology required is implemented in Marmotta Platform , an open platform for linked data.

  `https://marmotta.apache.org/`

  `http://www.agent-software.com.au/products/jack/`.

## 3.11 Simulation

The following works aim to integrate the BDI model with a simulation component and with a simulation model.

- [66] presents the initial step to integrate a distributed discrete event simulation system with a framework for intelligent software agents. The simulation component is based on the high-level architecture (HLA) [51] and the agent component implements the BDI approach. Furthermore, the architecture is connected to a real-time information source, an on-line sequential Bayesian algorithm.

  **Technology** This framework was applied to a real-life monitoring system for a tunnel-boring machine excavation project, but there are no references to any implementation.

- In [80] a framework that allows BDI cognitive agents to be embedded in an Agent-based model (ABM) system is presented. The conceptual framework realises the integration of an off-the-shelf BDI system with an off-the-shelf ABM system. The framework acts as the glue between the two systems which work independently. The main issues to be addressed is the fact that the ABM is time-stepped and operates on a simulation clock, instead the BDI system is event-based and does not model time explicitly. The conceptual resolution is to make the ABM the "master" that calls the BDI system once each simulation cycle.

  **Technology** The support infrastructure along with the code required for a number of specific systems, and several example applications is freely available. `https://github.com/agentsoz/bdi-abm-integration` under LGPL-3.0 License.

## 3.12 Spatial Concepts

Although the efficiency of belief, desire, and intention (BDI) architecture of agents is validated in varieties of sciences, its uses in Geospatial Information Systems (GIS) and specifically among spatial planners is still burgeoning [9]. The following works integrate spatial concepts to the BDI model.

- The goal in the works [8] and [9] from the same authors, is to develop a BDI agent based model to handle spatial issues. The fundamental concepts of practical reasoning architecture such as belief, desire, intention, along with commitment ad interaction, have been combined with analyses and applications of GIS. In [8] a Desktop GIAgent software is introduced, with the advantage of using agents for spatial analysis. In [9] particular attention is given to land use planning defined by three main components: land areas, goals and actions, translated to a spatial BDI agent architecture.

- In [91] a novel architecture is proposed in which an axiomatic derivation system in the form of first-order logic facilitates declarative explanation and spatial reasoning. The objective is to describe and develop an architecture that combines a multi-agent system with GIS, logical deduction and qualitative reasoning. The systems integrates multiple moving agents and the concept of means-ends spatio-motional reasoning. The paper provides details about the architecture and simulation system for moving reasoner agents (SISMORA).

- The work presented in [16] comprises the design and implementation of an integration of a conceptual-space level into the BDI agent architecture, with the aim of helping people who are blind or visually impaired to know where they are, where they want to go and how to get there safely and independently.

**Technology** This integration is developed on top of the resources of the Jason platform and the CSML API. The CSML language is presented in [1] and the APIs are supplied. The API provides resources to create, compare, manipulate and validate CSML content with the aid of a reasoner.

`https://github.com/jason-lang/jason` under the LGPL-3.0 License and continuous to be updated.

- The paper [7] presents SOLACE (SOciaL Attachment Crisis Evacuation), a multi-agent model of human behaviour during seismic crisis based on social attachment theory, where real geographic data are used to define the spatial context of the crisis environment, delimit mobility with barriers and constrain movement to free space. The novelty of this model must be sought in the integration of social attachment and GIS data.

  **Technology** The model was implemented using the GAMA platform using a BDI approach. No references or repositories regarding SOLACE have been found.

  `http://gama-platform.org`.

  `https://github.com/gama-platform/gama` under GPL-3.0 License.

### 3.13 Extra

Finally, some works that do not fall under the macro-categories highlighted above.

- In [18] an integration of distributed transactions into the computational model of a multi-agent system based on the BDI architecture is proposed. The transactions are the foundation of the operational semantics of intentions and of collaborative tasks with team of agents. This way, a well defined notion of correctness exist at the semantic level, without the need of hardwiring robustness and fault-tolerant behaviour into agent plans.

- BDI theory is starting to be considered a promising tool for modelling sophisticated characters in Interactive Storytelling [69]. The use of BDI for modelling intelligent characters and develop a Narrative BDI extension to an existing character-based storytelling system is studied. The approach is based on a real-time planner whose operators mainly deal with literary feelings.

- In [70], a policy to express high level business requirement of grid computing system, is integrated into agent BDI model to reflect changing requirement of business application. Policies are imported as external motivation into the traditional agent model. A logic language $L_p$ for P-Agent representation is defined based on the BDI logic described in [73] which is an extension of CTL* logic. A model of PGrid, an open architecture which supports grids and grid applications, is proposed.

- In [25] a possibilistic approach to BDI is presented using a possibilistic framework. Using this framework is possible to represent partially sure beliefs and partially desirable world states. A possibilistic representation of beliefs and desires is introduced and the agent mental state is defined.

  **Technology** A repository regarding this framework was found on github after some research.

  `https://github.com/tettaman/kobdig` under BSD-2-Clause License.

- In [78] an integrated model was developed building on the BDI model and the social influence theory, with particular attention to the concept of we-intention.
- The paper [75] presents CISM@, a Cloud computing Integrated into Service-Oriented Multi-Agent architecture. CISM@ integrates intelligent agents with a service-oriented philosophy in order to provide Cloud Computing services, both at software (SaaS) and platform (PaaS) level. The functionalities of the system are modeled as distributed services and applications invoked by the agents.

# 4 Analysis

A summary of the data collected can be viewed in the table 3 and the legend of the terminology can be checked on table 4.

# 5 Discussion

An answer to each research question based on the results collected and the analysis carried out.

## 5.1 Q1: Which integration categories are the most widespread?

This question expresses the main interest of this Systematic Literature Review.

To answer this question, primary studies were collected and consequently divided according to the category they belong to. PMs may have to deal with topics relating to several categories, in those cases the one that was considered most central to the objectives of the article was chosen as a reference, but the others were also considered, see the note on table 3.

The categories are first discussed in section 3, where for each category the studies that are part of it are presented. A more concise view can be examined in table 3.

To summarize the results found, in alphabetical order: out of 72 PMs, 4 were focused on the way agents make decision (Decision Making), 5 took into account the agent's emotional mental states (Emotions), 3 described different mechanisms of intention selection (Intention Selection), 5 were based on the use of different logic (Logic), 6 have incorporated the ability to learn into the model (Machine Learning), 6 have integrated different kind of models to the BDI one (Model), 7 have addressed the planning limitations (Planning), 7 proposed probabilistic reasoning capabilities (Probabilistic), 6 discussed ways to improve the reasoning abilities of agents (Reasoning), 6 aimed to increase the knowledge available to agents by means of semantic web ontologies (Semantic Web), 2 works incorporated a simulation component and a simulation model to the BDI model (Simulation), 5 have integrated spatial concepts, predominantly through the use of Geospatial Information Systems (Spatial Concepts), finally 6 extra works have been considered (Distributed Transactions, Interactive Storytelling, Policy, Possibilistic, Social Influence Theory, Cloud).

If we also consider those studies that deal with several categories, without considering only the main one, the final count is: 4 Decision Making, 7 Emotions, 3 Intention Selection, 7 Logic, 9 Machine Learning, 11 Model, 8 Planning, 10 Probabilistic, 6 Reasoning, 6 Semantic Web, 3 Simulation, 5 Spatial Concept, 6 Extra.

Some papers are not considered in table 3 and in this summary because extensions or argument of other considered papers, but are discussed or referenced in section 3.

| Analysis | | | | |
|---|---|---|---|---|
| | **N°** | **Integration** | **Technology** | **Project** |
| **Decision Making** | [46][52][65]<br>[90] | [46] = Coherence-driven adaptive<br>[52] = Internal Performance<br>[65] = Recognition-primed<br>[90] = Inner decision | [46] | [46] |
| **Emotions** | [10][15][40]<br>[72][87] | [10][15][40] = OCC<br>[72] = Perception-Action Model<br>[87] = Emotions and Engagement | [15][40] | [15] |
| | [37][88] | [37] = OCC<br>[88] = Ellis's ABC Theory | | |
| **Intention Selection** | [12][93][94] | [12] = Design-To-Criteria Scheduler<br>[93] = Plan coverage<br>[94] = Enablement Checking,<br>Low-coverage prioritisation | [12][94] | |
| **Logic** | [22][68][71]<br>[85][96] | [22] = Coalition logic<br>[68] = Propositional Dynamic Logic<br>[71] = Many-sorted first-order logic<br>[85] = Fuzzy logic<br>[96] = Deontic epistemic action logic | [85] | |
| | [50][70] | [50] = FODL, Priority Logic<br>[70] = Extension of CTL* | | |
| **Machine Learning** | [3][4][33]<br>[64][83][89] | [3][89] = RL<br>[4] = TDL, Q-learning, SARSA<br>[33] = TDL, Q-learning<br>[64] = LSTM<br>[83] = Adaptive ML | [3][4][33][64][89] | [3][89] |
| | [35][59][82] | [35] = Linear Regression<br>[59] = Intentional Learning,<br>Manipulative Abduction, RL<br>[82] = ACL, BUL | | |
| **Model** | [14][17][60]<br>[63][88][99] | [14] = CAB, FFM<br>[17] = Linear Threshold<br>[60] = Computational model<br>of selective attention<br>[63] = Biological Immune System<br>[88] = Psychoterapeutic Model<br>[99] = Petri Net | [14][17][88] | [17] |
| | [5][37][50]<br>[71][80] | [5] = Event-based run-time model<br>of institutions<br>[37] = ReGreT<br>[50] = BRS, ForTrust, ReGreT<br>[71] = Repage<br>[80] = Agent Based Model | | |
| **Planning** | [29][35][59]<br>[67][77][82]<br>[98] | [29] = Case Based Planning<br>[35] = Machine Learning<br>[59] = Intentional Learning<br>[67] = Specifications<br>[77] = Genetic Algorithms<br>[82] = Decision Tree<br>[98] = First-Principles Planning | [35][59][67][77][98] | [67] |
| | [83] | [83] = Decision Tree | | |

<table>
<tr><th colspan="5">Analysis</th></tr>
<tr><th></th><th>N°</th><th>Integration</th><th>Technology</th><th>Project</th></tr>
<tr><td rowspan="2">Probabilistic</td><td>[6][23][27]<br>[54][58][74]<br>[79]</td><td rowspan="2">[6][74] = POMDPs<br>[23] = Bayesian Networks,<br>Influence Diagrams<br>[27] = Bayesian Theories<br>[54] = BBN, DFT, PDFS<br>[58][79] = Bayesian Network<br>[29] = Bayesian Networks<br>[40] = Bayesian Decision Networks<br>[66] = Bayesian Algorithm<br>[82] = Probabilistic<br>plan selection function</td><td rowspan="2">[6][23][54][58][79]</td><td rowspan="2"></td></tr>
<tr><td>[29][40][66]<br>[82]</td></tr>
<tr><td>Reasoning</td><td>[5][37][47]<br>[50][53][95]</td><td>[5] = Event-based run-time model<br>of institutions<br>[37] = Trust processes<br>[47] = Organizational Reasoning<br>[50] = Trust model<br>[53] = NARS<br>[95] = Case-based reasoning</td><td>[5][47][53][95]</td><td>[47]</td></tr>
<tr><td>Semantic Web</td><td>[20][41][42]<br>[44][55][56]</td><td>[20] = Linked Data<br>[41] = Rule Interchange Format<br>[42] = Description Logic<br>[44] = OWL, RDF<br>[55][56] = OWL-S</td><td>[20][44][56]</td><td></td></tr>
<tr><td rowspan="2">Simulation</td><td>[66][80]</td><td rowspan="2">[66] = High-level architecture<br>[80] = Agent Based Simulation system<br>[54] = AnyLogic 6.0</td><td rowspan="2">[80]</td><td rowspan="2">[80]</td></tr>
<tr><td>[54]</td></tr>
<tr><td>Spatial Concept</td><td>[7][8][9]<br>[16][91]</td><td>[7][8][9][91] = GIS<br>[16] = Conceptual space markup language</td><td>[7][16]</td><td></td></tr>
<tr><td>Extra</td><td>[18][25][69]<br>[70][75][78]</td><td>[18] = Distributed Transactions<br>[25] = Possibilistic framework<br>[69] = Interactive Storytelling<br>[70] = Policy<br>[75] = Cloud computing<br>[78] = Social Influence Theory</td><td>[25]</td><td>[25]</td></tr>
</table>

Table 3: Analysis of the study results. **Notice**: If two rows appear in correspondence with a category, you should read as follows: the upper row refers to the studies of the category, the lower one to the studies of other categories that also deal with that topic. For the lower ones, the technological correspondence is not evaluated because it has already been counted in the related category.

| Legend | |
|---|---|
| OCC | Ortony, Clore, and Collins theory |
| FODL | First-Order Dynamic Logic |
| CTL | Computation Tree Logic |
| RL | Reinforcement Learning |
| TDL | Temporal Difference Learning |
| SARSA | State–Action–Reward–State–Action |
| LSTM | Long Short-Term Memory |
| ML | Machine Learning |
| ACL | Aggressive Concurrent Learning |
| BUL | Bottom-Up Learning |
| CAB | Culturally Affected Behavior |
| FFM | Five Factor Model |
| BRS | The beta reputation system |
| POMDPs | Partially Observable Markov Decision Processes |
| BBN | Bayesian Belief Network |
| DFT | Decision-Field-Theory |
| PDFS | Probabilistic Depth-First Search |
| NARS | Non-Axiomatic Reasoning System |
| OWL | Web Ontology Language |
| OWL-S | Web Ontology Language for Services |
| RDF | Resource Description Framework |
| GIS | Geographic Information System |

Table 4: Legend relating to the terminology used in table 3

## 5.2 Q2: Are there technologies to support these integrations or just the models are described?

For each PMs, when present, a description has been added in section 3 regarding the technologies used: if provided, or found after a short search, the related links and licenses have been reported.

The results are listed in table 3 with the reference to the works providing a technology and to those supplying a project repository or homepage.

Of all the PMs reviewed, 35 defined the technology used in their work by referencing it or providing a repository. Out of these 35, only 9 (25.71%) provided a project repository regarding their work.

Most studies limit themselves to present a conceptual model, which can serve as a starting point for developing new technologies in the future.

## 5.3 Q3: Are these technologies effectively used in real-world applications?

Most of these works are based on existing technologies that allow the development of MAS: Jadex, Jason, JACK, GAMA, JaCaMo, BDI4Jade, CArtAgO. As pointed out in a related-work [21], aside from JACK, the other technologies are not used in real world, but it can be argued that technologies like Jason and Jadex might be ready for this use.

These technologies are then extended or integrated with others of the related category of integration: DecoAgent, NRC FuzzyJ, NetLogo, JGAP, Fast-Forward, AnyLogic 6.0, Netica, JAMA, SOAR, Hugin, NARS, SPARQL, Marmotta, ABM.

Also some extension of AgentSpeak have been presented: AgentSpeak+, AgentSpeak(PL), AgentSpeak(XL).

Among the projects that have been created by exploiting these integrations, those that are actually used in real applications are few.

The framework in [66] was applied to a real-life monitoring system for a tunnel-boring machine excavation project. The architecture described in [29] and [28] has been implemented in a real scenario to classify leukemia patients. But that said, there is no evidence to show further uses of these technologies.

Even if the evidence of use is minimal, these technologies are a starting point to demonstrate the potential of the BDI model and the uses that can be made of it in the future, defining interesting research areas.

# 6 Conclusion

The Systematic Literature Review is a powerful tool that allows you to obtain a general and methodological view on a certain topic of interest. This work followed the standard SLR methodology, making sure the whole process was documented and easily reproducible. I have collected by hand a body of papers starting from four digital libraries (Google Scholar, IEEE Xplore, Springer Link, ACM Digital Library), by submitting them two different queries each. The whole process was documented by writing the results on excel sheets. The collection has been filtered by hand using inclusion and exclusion criteria and following precise steps. Everything is documented in section 2.

At this point the primary studies were analyzed and the work was organized as follows: in section 3 each paper has been described and assigned to a category, where provided, the related technology have been reported. The results were then analyzed and summarized in table 3.

At the end of this research, what emerges is that there are various types of integrations applicable to the BDI model, but still few technology ready to use or projects available, especially with regards to real world applications.

There are related-works, for instance the work in [21] provides a comprehensive view of logic-based technologies for MAS, [13] puts its focus on identifying a range of possible approaches to integrating AI into a BDI agent architecture by organizing the work in: AI in the sense phase, plan phase, act phase and discussing the architectural strategies for integrating AI in BDI agents.

Having said that, this work aims at different objective, that of categorizing the types of integration in order to understand in what ways the BDI model can be augmented and in what fields it can be used. In this way, i believe this SLR could become the starting point for defining new research areas and future projects.

# 7 Attachments

## 7.1 Paper List

A public group on Mendeley with all the references to the Primary Studies: `https://www.mendeley.com/community/slr-bdi-integration/`

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