A Survey of Pedagogical Functions of Intelligent Agents in Virtual Learning Environments

MOHAMED SOLMAN
Institute for Information Systems and Computer Media
Graz University of Technology
AUSTRIA
Muhammed.soliman@gmail.com

CHRISTIAN GUEHL
Institute for Information Systems and Computer Media
Graz University of Technology
AUSTRIA
and
School of Information Systems and Computer Media
Curtin University
Australia
Christian.Guehl@item.tu-graz.ac.at

Abstract

This paper provides a literature review and perspectives on employing Intelligent Agents for human learning in virtual learning environments. The paper provides: 1) Research literature that employs AI functions and methods for educational or training purposes by the use of Intelligent Software Agents. 2) Analysis of the pedagogical functions; pedagogical gain of employing pedagogical agents. Selected essential topics to learning with agents are investigated including personalization with intelligent agents, cognitive and meta-cognitive agents for teaching, emotions and affections of embodied pedagogical agents and agents as virtual humans. Applications of using intelligent agents are demonstrated from an educational perspective.

Keywords: Intelligent Pedagogical Agents, Cognitive Tutors, Intelligent Agents.

1 Introduction

The current use of technology in education has provided values to distant learners. While there is the proliferation of the tools to education, still there are very promising areas to improve specially in considering teaching effectiveness as a goal. Tools for collaborative learning, adaptive and personalized instruction, automated and semi-automated assessment provisioning, visualization, pedagogical guidance, and more all are possible but not yet fully utilized given their potential and value for instruction. There are particular values to the use of new advancements of ICT; scalability, reachability, convenience, and cost-effectiveness can make such tools wonderful to be utilized for teaching. However, the use of machines for learning can't substitute an experienced teacher. And therefore, the use of ICT in education has been used in ways that do not replace teachers, such as blended learning. But in the quest for using ICT for education purposes, researchers found great windows of opportunities in employing the machine to aid learning in an intelligent way as by utilizing AI in education. The use of the distributed and intelligent agent model can contribute with a new paradigm to serve those objectives.

For human learning, investigating the pedagogical foundation of the learning scenarios with technology is a necessity. For example, what makes collaborative learning very effective? How to guide learners digitally? How to motivate learners more? How to provide healthy and productive digital learning experiences? With those questions in mind, one can highly contribute to learning given the scalability, intelligence, automation, and availability of computing nowadays anywhere and anytime. One may also discover that there are new possibilities that were not possible in a classroom before.

This paper aims at surveying literature on multiple active software entities; named agents with pedagogical design purposes. Those agents are goal-oriented, are acting upon or with the
learners towards those goals by being equipped with intelligence abilities. Those entities can also interact and negotiate learning objectives. In our case the goals are pedagogical. The paper also considers investigating how the human mind think and learn and how learning can be supported by intelligent pedagogical agents.

Intelligent Pedagogical Agents (IPAs) have artificial intelligence (AI) capabilities that can support learning functions. The agent itself can be viewed as a focal point of interface between the learner and the environment with the supporting background functions. Research efforts found has targeted different relevant sub-topics, shown in this paper, with the efforts to integrate them.

Why Agents for education?
According to [1], an agent is a proactive and autonomous software entity. An agent has a sensing mechanism to respond to environment events. Agents also proactively act in the environment based on goals. The environment of inhabiting agents is named society of agents meaning there are multiple agents inhibiting a paradigm with dynamics of their interaction. Because there are multiple agent goals, and the autonomy of the agent behavior, the multi-agent model is a distributed computing paradigm. With that, agents may have different conflicting goals which give closer model to reality. Agents negotiate to resolve conflicts in order to achieve those goals or coordinate to achieve a collective task by coalition of different agent intelligence abilities. In the virtual learning environment, we have learners interacting with the environment and with back-end tools or software entities that can automate goals or provide learning services as possible to learning. The goals can be individual learning goals or organizational learning goals. The agents can be viewed as dynamic gluing mechanisms to those goals with their autonomous and proactive nature not existing in other paradigms. The use of agents is an excellent model for a distributed learning environment that provides a balance and solution between individual learning goals and the environment facilities and constraints. And therefore it is needed for a new generation of learning environments that is different from a single learner-to environment interaction model. This will be demonstrated among different research efforts found in literature.

In summary, agents have the following characteristics:
- Act autonomously towards a goal, without direct control. A group of agents can act & interact autonomously in the system to reach a goal.
- An autonomous agent can act as a common interface with the learner.
- Decentralized intelligence. Help to take decisions by considering other recourses.
- Balance individual goals against common goals.
- Negotiate and cooperate of information, intentions, and goals.
- Perform tasks not possible in individual software / user by working with the environment and other event generators.

Based on these properties, several research efforts attempted utilizing them to improve learning or training. The objective of this literature review is to reveal this topic in particular to include better utilization of pedagogical agents in electronic learning environments.

The paper is organized as follows: Section 2 reviews the topic of agent-based personalization which took other forms presented in other sections. Section 3 reports adding emotion functions and affection to learning environments by using intelligent agents and reports research found. Section 4 is focused on cognitive and meta-cognitive agents, what research has been done and how it supports the learning process from different aspects. Section 5 discusses research when agents are embodied to provide visual appearance and discusses relevant issues. Section 6 is concerned with surveying pedagogical functions as a result of interaction among different agents. Section 7 sums up important conclusions and outlines further work.

2 Agent Based Personalization

Education theories and practice support understanding and treating the learners individually according to their specific capabilities. In electronic environments, personalization provides effective learning. See
Furthermore, as learning occurs by building associations based on prior knowledge then the prior knowledge is different from one learner to another depending on the environment the learner was exposed to and other factors. The use of the agent model is a pillar to personalization as as an agent is seen as the focal point of interaction/interface between the environment and the individual learner. Authors in [3] built a system of multiple interacting intelligent agents (based on the Java Agent Development Environment, JADE) to support adaptation based on learning styles and objects. This system is composed of five different interacting agents: Student Agent, Record Agent, Evaluation Agent, Learning Object Agent, and a Modeling Agent. All have a common general goal of personalization. The system provides a segregation of agent duties as the student agent for example is responsible for communicating with the learner (through a communication layer) in the agent design. The evaluation agent is responsible for ensuring an individual and adaptive learning path. However, it didn’t provide implementation results and the interface agent did not take any form of embodiment. Personalization is provided in [4] by an interface agent that interacts with another agent that implements Item-Response-Theory (IRT agent). IRT is an assessment mechanism that provides and estimates the learner abilities through learner feedback. This research is an example of what the pedagogical agent can provide personalization by interacting with the personalization mechanisms through agent technology. [5] argues that agent systems provide ultra-personalization of the learning process in a decentralized way. The basis for the argument is that agents can represent the requirements of the learner in a virtual learning environment and then negotiate to achieve the those requirements in a decentralized fashion. For example, personalization has initially taken several forms in Intelligent Tutoring systems. Selection of courses and sequencing based on learner assessment results are forms of personalization in ITS. We are interested in the distinctive aspects of Pedagogical Agent-based personalization.

Personalization also means treating online learners differently based on their different abilities which is inherent in different aspects of research as found in the subsequent sections as well.

3 Emotion, Affection, and Believability of Pedagogical Agents

Emotions play a significant role in learning. For example, learner motivation is highly affected by his emotional state and can lead to higher learning results. Human emotions are complex to understand with its own theme of research. Research by [6] reported that emotions have effects on human decision making ability in learning. The authors showed that traditional AI capabilities can be extended by artificial emotion research and hence it took its share in AI research. Affective computing became an established research theme of Artificial Intelligence that works with finding computational emotion models. There have been several steps taken in integrating emotions in artificial virtual agents to improve HCI with the learner. Embodied agents and virtual characters have been usually researched and are still under investigation for learning purposes. Providing gestures and animations of the pedagogical agent or providing conversations with the learner are of interest to the researchers in the fields as will be shown later. Adding emotions adds believability to personification aspect thus enhances learner engagement.

Traditionally another evidence of the importance of emotions in learning is found in the famous model of Bloom’s taxonomy for educational objectives as it includes the affective domain that involves emotions. Emotional modeling tries to understand emotions and build a computational model with the emotion states and their triggers. The OCC model of emotions by [7] (throughout this paper, the term OCC will refer to this model) has been found to be widely used among researchers of emotional modeling. This research provided an organization of emotional states and how they are triggered, see Figure 1.
Empathy is a strong mutual reaction that occurs in a social interaction. [10] studied social effects of emotional pedagogical agents on learning and on decision making in particular. It considers five emotional states (facial expressions) of an agent: neutral, joy, sadness, shame, and anger. It also studied the effects of agent emotion dynamics according to the environment situation and its effects on the cooperation and interaction with the human. The study showed that “participants are sensitive to differences in the facial displays and cooperate significantly more with the cooperative agent”, [10]. One conclusion is that emotions influence the HCI interaction as it adds a new channel to listening or viewing. People can infer information looking onto facial expressions. It is worthwhile noting that the agent is a central concept to include emotions in virtual learning environments as it is the only possible representation to emotions to it. Research has shown that adding a human (creature) shape to the interface in the learning environment can improve interaction with the computer. This has been extended to 3D virtual environments through embodied agents which are 3D characters that try to simulate the human, as will be discussed. Conversation, animation abilities have provided improvements. Believability of the agent can lead to better interaction and learning results. Studies with the Persona Effect have shown that learners are engaged more with agents that express emotions; see [from 10].

The Politeness Effect
Research with politeness of the facial expressions of the pedagogical agent investigates the effects of politeness to the learner as an extension to the previously mentioned persona effect. [11] discussed the foundation for the politeness theory (based on Brown and Levinson (1987)) in social intelligence within the scope of pedagogical agents. The Brown and Levinson theory of politeness differentiates between the positive and negative face threats on learners. [11] regards the politeness effect as a major motivational drive for the learner and report higher learning outcomes with polite pedagogical agents compared to non-polite ones.
The same research stresses the significance on the politeness effect compared to the persona effect.

**Emotional State Evaluation**

Determining the emotional state has two sides; the emotional state of the pedagogical agent and the emotional state of the learner, and then how they are elicited. The emotional state of the pedagogical agent can change according to the emotional state of the learner (with empathy for example) or according to events occurring in the environment. Change in the emotional state is referred to emotional elicitation and it can occur due to a change event in the environment, belief or intentions, see [9]. It is possible to find about the user emotional state through pattern recognition after capturing the face picture since it is evident that emotions change facial expressions or by specialized sensing/measuring devices attached to the human body (wearable devices), or inferred from user beliefs, intentions as used in several research works. [11] summarized, from research, methods to infer user emotion states, see Figure 2. This determination of the learner emotional state if used properly as an input to pedagogical agents’ affection, can improve learner interaction, learner attitude towards learning and lead to better learning results. The research work by [11] contribute affective tactics of agents based on the Belief-Desire-Intention model, BDI. Affective tactics occur as a result of events occurring in the environment. They analyze those tactics according to intrinsic or extrinsic motivation toward learning and the resultant behavior. The choice in this research of the BDI is based on the possibility of cognitive understanding of emotions. This choice can be fortunate as the BDI model is implemented in agents and can be integrated with other cognitive skills.

![Figure 2: Four methods of capturing user emotional states, adopted from [11].](image)

When working with emotions becomes possible and automated, pedagogical agents are needed for:

- Increasing believability within the learning environment
- Engaging the learner and capturing attention
- Elevating emotional state (remove frustration caused with difficulties or failure) maybe by empathy – affective tactics
- Alleviating negative emotional states and creating positive learning situations
- Determinations of emotional states and learning moments that can negatively impact learning
- Improving motivation: providing appraisal and suppressors for learning

### 4 Cognitive and Meta-Cognitive Agents

Cognition refers to the process of human thought. It involves understanding how the mind works. In research there were significant efforts in cognition research that led to different education theories. On the other hand there were several efforts to build cognitive models with agents. Scholars such as Allan Newell laid the foundation to unified cognition theories that have been used later with agents creating SOAR
architecture. STEVE, the pedagogical agent was created based on SOAR. Another famous system is the ACT-R cognitive architecture developed at Carnegie Mellon University. [13] provides a history, introduction & review to cognitive architectures and inspiration into biological-based cognitive architectures. It provides a rationale for the necessity of understanding human cognition in order to provide effective tutoring systems. Evidently understanding the learner and how learning works lead to effective learning. Not only that, but understanding the human cognition lead to building artificially intelligent entities that simulate the human brain. Definitely, fully understanding human cognition and building a complete model is far away to reach while researchers try to find accurate models. Those models can help us build co-cognition between the pedagogical agent and the learner. [13] points the challenges researchers face with this understanding that has to several theories of cognition. Researchers in those domains try to employ cognitive architectures (and emotion ones as discussed) with the agents. Cognitive tutors are agents with cognitive architectures mainly adopted in Intelligent Tutoring Systems. ACT-R is an example cognitive tutor agent based on the ACT-R theory developed at Carnegie Mellon University. Researchers have pointed the importance of building architecture of cognitions rather than a single entity. [14] indicated that the agent model is a suitable model of building a cognitive architecture and provides the IDA (Intelligent Distribution Agent) based on the Global Workspace Cognitive Architecture (GW)\(^1\).

Another relevant area is teaching an agent with the concept map. In other words, understanding the learner and how he learns is essential to human learning. Understanding how knowledge is constructed will lead to designing effective teaching methods. Relating to prior knowledge by a schema of prior concepts has an influence on adaptive systems that present tailored instruction. The critical thinking methods compliant with cognitive theories can lead to agent design methods with an agent providing contradictions stimulating thinking and leading to better established knowledge. Thus it is also important to consider cognitive disequilibrium as well. [13] proposes the following definition of an ideal artificial cognitive tutoring agent: "an agent built on an architecture that offers structures, features and functioning comparable to the human model so that it is similarly capable of adaptation, learning, generalization within and across domains, and action in complex situations encountered in tutoring learners".

### 4.1 Conceptual Change Agents

Conceptual change is an important and evolving learning approach especially to science education. Conceptual change involves deep changes of one's knowledge. And therefore concepts and their relationships change over time. It can involve being exposed to contradictions and critical thinking to reach cognitive equilibrium according to Jean Piaget constructivism theories. This equilibrium can be exposed to new set of conflicts through conceptual change leading to a new cognitive equilibrium (better established knowledge). This research follows and important concept to construction of knowledge by posing cognitive disequilibrium. [15] proposes the integration of conceptual change in animated pedagogical agents. Learners perform experiments and are given an opportunity to generalize (model) the experiment by linking graph nodes of concepts thus creating hypotheses. The pedagogical agent will foster conflicts and thus stimulate the conceptual change for the learners. It is imperative to refer to BDI agents by having what is called belief revision as old beliefs are revisited and change accordingly.

While learning is a social activity, social interactions have a learning component. i.e. we can learn by social interactions with others and this means influencing each other concepts, possibly discussions and argumentations are triggers for concept change leading new equilibrium. Distributed cognition vs collective cognition looks at surrounding objects and group of individuals rather than individualized learning ones. Study of this model is relevant to multi-agents and the social virtual environment.

---

\(^1\) The GW theory focuses on consciousness and unconsciousness
4.2 Bayesian Networks for Agent Learning

Bayesian Networks, BN is a common probabilistic AI method. It is also referred as Belief Network. It is represented as a directed acyclic graph. Each node represents a belief or hypothesis (as a random variable) and edges represent conditional dependences between them and therefore it can be used for inferences and learning. The BN learning problem is inferring the structure of the graph from data, which is not a trivial problem. BN is a popular model with several successful applications. Our main interest is the machine learning application and issues relevant to understanding the learners and their cognition and dynamically dealing with it through time. Influence Diagrams also named Dynamic Decision Networks, DDN are variations to BN. Influence Diagrams or DDNs are used to solve decision problems under uncertainty, described below.

This model has been used by researchers as a method of inferring learner abilities and thus providing tailored (adaptive instruction) to the learner. Not only the Dynamic Bayesian Network model has been used by [16] to have a learner model, but it was also through a pedagogical agent. The choice of the pedagogical agent was due to evidence of increased learner engagement and improved learning. That learner model considers cognitive, meta-cognitive abilities and emotions. Upon constructing the DBN, reasoning about learner knowledge levels is done and used by the pedagogical agent to provide guidance to the learner. By having more information (through this model) about the affective state of the learner, the purpose of that study is to have better informed pedagogical agent interventions. This work provides relevant details such as what DBN to keep, short term and long term student models, and an evaluation of the results.

[17] equips pedagogical agents within the scientific inquiry learning environments (INQPRO) with Dynamic Bayesian Networks. In this model, the probabilistic Bayesian Network Model is used to model learner properties as it changes through time (due to learning or conceptual change mentioned above). Learners interact with the learning lesson as a computer simulation by the aid of a pedagogical agent. At this stage, a mental model is constructed. Then a discrepancy is presented (through the simulation). The pedagogical agent will monitor the following interactions through this process of conceptual change leading to conflict resolution stage. In this work, the probabilistic nature of capturing mental states is tackled by the use of Bayesian Networks and the conceptual change mandated it to be of a dynamic nature. However, the work didn’t show the accuracy of detecting the learner concepts. It did not provide details of the efficiency of the results obtained or compared to other methods. It also did not consider emotions.

The purpose of the DDN (Dynamic Decision Networks) according to the research by [18] is to support scientific inquiry by reasoning about learners abilities and provide learning support. A special feature of the DDN is its ability to deal with the temporal aspects captured during interaction with the system, [18]. The DDN concept has been used in several tutoring systems for predicting learning abilities such as knowledge, focus of attention, affective states, and actions taken. A Decision Network is an extension to the Bayesian Network by adding Utility and Decision Nodes. DDN are changing DN’s over time. Peedy, the pedagogical agent uses DDN in the INQPRO learning environment. Common to these research efforts with BN, or DN or conceptual change model is trying to capture the cognitive states or concepts or mind states of the learner by observing behavior (interaction with the system).

4.3 BDI Agents for Human Learning

BDI, the famous Belief-Desire-Intention model has been widely adopted in agent-based systems. Its origin comes from AI Agent research (see [1]) as it encodes agent behavior though setting goals that determine Desire and the Intentions. BDI model is composed of a set of logic rules (formalisms). It can be thought as a cognitive encoding of the agent (core component). The agent will have a mental state.
Table 1: Belief-Desire-Intention, from [11].

<table>
<thead>
<tr>
<th>Beliefs</th>
<th>Desires</th>
<th>Intention</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beliefs represent the information about the state of the environment that is updated appropriately after each learning action.</td>
<td>Desires are the motivational state of the system. They have information about the objectives to be accomplished.</td>
<td>Intention is a desire that was chosen to be executed by a plan, because it can be carried out according to the agent's beliefs (because it is not rational that the agent carries out something that it does not believe). Plans are pre-compiled procedures that depend on a set of conditions for being applicable.</td>
</tr>
</tbody>
</table>

Since the BDI model is used by agents to learn behavior (Behavior that leads to achieving goals), it can be used for a useful learning method by explanation. [19] utilizes BDI agents to generate three algorithms for explaining the agent behavior to the user. It uses an agent paradigm with BDI agents (GOAL) for that purpose. This work relates the reasoning chain to a result to show how the agent has reached that state thus achieving an explainable agent for training/learning purpose.

[20] extends cognitive encoding in pedagogical agents to add the emotional dimension of the learner (through adding emotions to the learner profile). The affective domain in the learner is explored through mental states of the learner exploited by the use of BDI-based agents. This allowed researchers to model mental states and their complex interactions allowing describing agent complex activities. Reasoning about student current emotional state is very important in the classroom and in electronic environments as well. The tutor can utilize those states to improve motivation, restrain about stressors and it may provide stressors in specific situations that can improve learning. [11] also utilizes the inference power of BDI to reason about the student emotions given its dynamic nature. The system needs to know events in the environment, the student’s goals, and the desirability of the events according to student’s goals. [21] extends the BDI model integrating the emotional dimension to the EBDI (Emotional BDI) architecture. The model describes interactions between beliefs, desires, and intentions with emotions during the deliberation process.

4.4 Meta-Cognitive & Self Regulated Learning Agents

Meta-cognition is an important topic to learning. Meta-cognition (thinking about thinking) and is related to learning improvement as it calls for learners awareness of their cognitive abilities and learning gains. Critical thinking for example is related to meta-cognitive ability. Self Regulated Learning, SRL is also a meta-cognitive activity. SRL means learning that is guided by meta-cognition (& strategic actions, evaluating, and motivation to learn). The importance of this subject is for learners to be self-guided and self-directed learners having learning goals directing them by having self-control of cognitive processes. Self-guided or Self-regulated learning concepts as we believe is fundamental to analyzing what we can create with virtual learning environments with the lack of human teacher but being subsidized with artificially intelligent agents. Therefore, one can seek to understand how SRL and meta-cognition in general is handled in the virtual learning environment.

[22] employs self regulated learning aided by Betty’s pedagogical agent. Betty’s System of SRL is shown in Figure 3. As shown, it provides knowledge construction and monitoring strategies. For example, information structuring meta-cognitive student activity is communicated to Betty’s system also through concept maps. Students also conduct monitoring meta-cognitive activities with Betty such as asking questions to the pedagogical agent (checking) and probing parts of the concept map with the pedagogical agent (Probing). In this research the pedagogical agent provided meta-cognitive feedback to the learners. While this study has provided study results to show that students perform better in knowledge construction strategy, it sheds light into the importance of developing monitoring meta-cognitive strategies to improve self-learning. The study also indicates positive results on learning by teaching a pedagogical agent.
4.5 Teachable Pedagogical Agents

Educators agree on the benefits of teaching as a tool of learning. Students learn twice when they teach. Psychology studies show why students pay extra attention and effort to teaching others, possibly due to taking responsibility and harvest social benefits. A Meta-cognitive benefit occurs to the learner when he teaches others due to reflection and cognitive processes of teaching. In electronic environments, an added meta-cognitive benefit occurs due to the nature of teaching an agent. This is due to the ability to infer about student concepts and cognition to aid later for assessing acquired concepts and improve the current ones or possibly to know about the learning characteristics/abilities of the learner. The novelty of researchers' idea in this direction can come from the fact that teaching an agent can have feasibility more than of an agent teaching the user due to human vs. computation abilities but indeed there are pedagogical benefits. [23] reports two meta-cognitive aspects of learning by teaching: dual-task demand of meta-cognition (alleviating some burden of learning by teaching) and that in teaching responsibility as an important motive to involve students in meta-cognitive activities.

Personalization research has focused in the aspect of understanding the learning in different methods. Commonly by building a learner profile that tries to infer learner abilities by monitoring the learner behavior and interaction with the system. In contrary, teaching an agent in the environment can give a great opportunity for AI methods to know more in the learner. Research in teachable agents can also add to the aspect of understanding the learner since the teachable agent (can be a trusted companion) can give the opportunity for the learner to reveal what she believed and the agent side can use AI methods to infer the learner conceptions and misconceptions. The result of course will be used for further learning.

Betty's Brain is also a teachable agent developed at Stanford AI labs, [24]. It uses concept maps. The student teaches Betty a concept map through a graphical interface. An interesting feature in the system is that the student asks Betty questions, Betty can answer from the given concept map. But Betty's inability to answer questions will trigger and motivate the student to learn more so as to teach it to Betty. Students get scaffolding functions by other agents.

The teachable agent group at Vanderbilt University conducts research in the area of teachable agents. They extend the use of Betty for further research including measuring Self Regulated Learning (SRL) results with teachable agents and building Hidden Markov Models, HMM generated from student activity sequences as a result of interaction. (HMM is a similar method or a variation to Bayesian Networks).

[13] mentions other methods of representing knowledge dealt with agents including several cognitive-based architectures including semantic networks.

Compared to Bayesian Networks, the use of the deterministic concept map teaching to an agent can solve the problem of reasoning under uncertainty of BN since it is not a behavior observation approach, no inference errors occur.

5 Models of Multiple Interacting Pedagogical Agents

Now it is important to look into the group aspects of pedagogical agents (IPA-IPA interactions), the models supporting this aspect, and what has been done in research. Electronically, a well structured society of pedagogical agents (Multi-agent system) is needed to provide support to agents, set common goals, resolve conflicts, and direct to new recourses, and assign agents to learners. Researchers have used a pedagogical agent as a character or as an autonomous software entity. Agents occupy an
agent society. We can also look into group aspects of the learning environment including curriculum design based on other needs and so on. We believe this aspect has a distinguishing factor for electronic based learning than traditional one as it can has a shorter cycle of assessing learning status and outcomes versus objectives. It can significantly provide faster group learning adaptations to changes in the environment and needs.

In designing Agent-Based complex systems, we use agent-oriented software engineering, AOSE. Several approaches have been used in research. See for example, the goal-net architecture for project river city. The GAIA MAS system design methodology has been suggested by [25]. An illustration of the developing levels of MAS by GAIA methodology is depicted in Figure 4, [26].

![Figure 4: Overview of the GAIA Methodology, from [26].](image)

It starts from global requirements (can be collective pedagogical objectives) to the global behavior and working down to individual agents, their coordination, and associated services. Therefore, it is a gluing design mechanism that puts organizational goals first. This model provides an autonomous software organization model that can be suitable for multiple pedagogical agents. The design of pedagogical MAS including GAIA and others involve definition of different agent roles as described in research surveyed below.

GAOOLE (Gaia Design of Agent-based Online Collaborative Learning Environment) is a proposed prototype of an agent based tutoring environment based on the GAIA methodology with the Java Agent Development Platform (JADE), [27]. There are five models described in this research; environment Model, roles model, Interaction model, agent model, and services model. The main goal is for collaborative learning which is surveyed in another section. Please see [27] for more details. [28] provides rationale and importance of the AOSE adoption for designing learning environments in MAEVIF (Model for the Application of Intelligent Virtual Environments to Education). In this research the Design of the system incorporates four modules; Expert Module for concepts, Tutoring Module, Student Module, and Communication Module. With Agent-Oriented Design, four different agent roles are given for each module and an added world agent (for interaction with the 3D environment). As a recommended with this study, the GAIA methodology was appropriate for the design of the environment according to the requirements mentioned. A resulting five agents’ model was formed:

- A Communication Agent
- A Student Modeling Agent
- A World Agent
- An Expert Agent
- A Tutoring Agent

5.1 Integrating Multi-Agent Systems with 3D Virtual Learning Environments

With the proliferation of Immersive and 3D VLE and Virtual Worlds, it is becoming important to integrate the MAS functions within the visual environment. In [28], the world agent role is dedicated to providing navigation and pedagogical interactions’ support with 3D objects inhabiting the 3D environment.

5.2 Virtual Teams Training with Pedagogical Agents: Intelligence Support

[29] proposes an architecture for training teams by the use of mixed teams of humans and BDI agents. The use of mixed teams means mixing virtual humans (agents) and real team players. The objective of this type of research (virtual teams training) is to enhance team performance to reach a common goal. It looks into both individual roles of team players as well as team
common objectives. In this problem domain, agents inhabit a virtual environment, their behavior is controlled individually and according a group objective. Therefore, this is looked as an extension to virtual humans by looking into groups rather than individual ones. And thus it supports decision making in the environment. Behavior is generated as a result of cognitive model. The ATOM model is identified by [30] for high performance team work. This model is used by [31] to identify where agents can support teams. The ATOM model suggests four dimensions; 1) Information Exchange, 2) Communication, 3) Supporting Behavior, and 4) Team Initiative/Leadership, See Table 2.

Table 2: ATOM teamwork dimensions

<table>
<thead>
<tr>
<th>Information Exchange</th>
<th>Communication</th>
</tr>
</thead>
<tbody>
<tr>
<td>- Seeking information from all available sources</td>
<td>- Using proper phraseology</td>
</tr>
<tr>
<td>- Passing information to the appropriate persons before</td>
<td>- Providing complete internal</td>
</tr>
<tr>
<td>being asked</td>
<td>and external reports</td>
</tr>
<tr>
<td>- Providing “big picture” situation updates</td>
<td>- Avoiding excess chatter</td>
</tr>
<tr>
<td></td>
<td>- Ensuring communications</td>
</tr>
<tr>
<td></td>
<td>are audible and ungarbled</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Supporting Behavior</th>
<th>Team Initiative/Leadership</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correcting team errors</td>
<td>Providing guidance or</td>
</tr>
<tr>
<td>Providing and requesting backup or assistance when</td>
<td>suggestions to team members</td>
</tr>
<tr>
<td>needed</td>
<td>- Stating clear team and</td>
</tr>
<tr>
<td></td>
<td>individual priorities.</td>
</tr>
</tbody>
</table>

According to [31], the four dimensions are used as guidelines of what agents can do to assist the team and reach the team objective with high performance. For example, agents are integrated with teams to coordinate their efforts, assist the humans what to do, coordinate with other agents to achieve a common goal, and monitor communication among them. This work employs the Joint Intentions Agent model and agent coordination methods to create shared plans. This work demonstrates the importance of the agent role as a communicator of information as a result of events in the environment or conveyed by humans (push information). In our opinion, the use of push events communicated to the learner can improve the believability of the pedagogical agent and improve learner engagement in the virtual environment (such as in games). Although this work researches the team collective goals, it focuses on team behavior support rather than aiding the team member or the group to learn a complex task online, or co-construct knowledge (not mentioned in Table 2 above) but rather works in mission actions. For example, this work aims at can assisting and adjust member roles and actions and provide dynamic information for each team player in action.

Given the above mentioned research, one can conclude that agents (in an MAS) can be used for team training. The distributed model while guiding agents to common goals, autonomy of an agent, ability to interact with the environment and correct beliefs, ability to have a joint-intention an coordinate actions all can lead to train a team to a high performance. Agent-interaction and cognition abilities for group behavior modeling and control demonstrated in virtual environments. Similar efforts can direct for example, training to run an assembly line or a factory, or run a machine by different operators by the use of agents in the virtual environment.

6 Conclusions and Future Work
Because of the inherent distributed nature of intelligence possessed by intelligent agents, they have been utilized for pedagogical functions. It was found that the proactively nature, the goal orientation, and the possible containment of intelligence, agents have been used for that purpose. Intelligent agents were used as cognitive tutors, teachable, and explainable entities. Thanks to the abilities of the agent to capture user interest and act autonomously on his behalf or with him dealing with other agents or other environment intelligence. Thus the agent could act as a companion or more because of the improved interaction that is also possible by adding cognition and emotion abilities. Furthermore, the agent social abilities nature has been used in research for pedagogical purposes exemplified by Multi-agents and pedagogical negotiation. It is found that those natures can provide pedagogical guidance and other significant pedagogical values to learners in distributed environments. It is our aim to utilize those features to enrich virtual learning environments pedagogically with agents' intelligence abilities.
References


ENTATION_GAIA.pdf


