ANALYSIS OF MODELS AND METACOGNITIVE ARCHITECTURES IN INTELLIGENT SYSTEMS

ANÁLISIS DE MODELOS Y ARQUITECTURAS METACOGNITIVAS EN SISTEMAS INTELIGENTES

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ABSTRACT: Recently Intelligent Systems (IS) have highly increased the autonomy of their decisions, this has been achieved by improving metacognitive skills. The term metacognition in Artificial Intelligence (AI) refers to the capability of IS to monitor and control their own learning processes. This paper describes different models used to address the implementation of metacognition in IS. Then, we present a comparative analysis among the different models of metacognition. As well as, a discussion about the following categories of analysis: types of metacognition architectural support of metacognition components, architectural cores and computational implementations.

KEYWORDS: Artificial Intelligence, Metacognition, Metamemory, MetaComprehension, SelfRegulation.

RESUMEN: Los Sistemas Inteligentes (SI) han aumentado en gran medida la autonomía en la toma de decisiones, lo que se han logrado gracias a la mejora de las habilidades metacognitivas. El término metacognición en Inteligencia Artificial (IA) se refiere a la capacidad que tienen los SI para el seguimiento y control de su propio proceso de aprendizaje. Este artículo describe diferentes modelos utilizados para abordar la aplicación de la metacognición en los SI. Luego presenta un análisis comparativo entre los diferentes modelos de metacognición. Así como, una discusión sobre las siguientes categorías de análisis: tipos de arquitecturas de metacognición que soportan los componentes de la metacognición, núcleos de las arquitecturas e implementaciones computacionales.

PALABRAS CLAVE: Inteligencia artificial, Metacognición, Metamemoria, Metacomprensión, Autoregulación.

1. INTRODUCTION

In recent years in Artificial Intelligence (AI) robust and Intelligent Systems (IS) have been developed. IS have highly increased the autonomy of their decisions, which has been achieved by improving metacognitive capabilities.

The term metacognition in AI refers to the capability of IS to monitor and control their own learning processes [1,2]. The metacognitive capabilities of IS are known in the specialized literature as "metacognitive skills" [3,4]. Metacognition is composed of three elements or components [5]: metamemory, selfregulation and metacomprehension, in which all the metacognitive skills are grouped.

Metamemory is about the capabilities and strategies that systems have to control and monitor their own memory processes. This is called selfawareness of memory [4]. SelfRegulation refers to the system's ability to make adjustments of its own learning processes. These adjustments are done in response to system perception about the feedback obtained from its current status of learning [5]. Metacomprehension is a specific application of metacognition. It refers to the degree of understanding that an IS has about the information that is supplied to it. [6,7,8].

Due to the importance that metacognition has for improving the performance of IS, this study seeks to answer the following question What issues of metacognition have been modeled in IS?

This paper is organized as follows: first a description of the more referenced metacognitive models in the specialized literature is given. Next, a summary table of the features about metacognition in these models is provided. Finally, we discuss categories of analysis and then present the main conclusions.

2. MATERIALS AND METHODS

The stages followed in the methodology of this research are described below.

2.1. Categories of analysis

To answer the research question, categories of analysis have been defined:

2.1.1 Types of metacognitive architectures

This category makes reference to the description of models, frameworks and architectures of metacognition, which have been proposed by several authors.

2.1.2 Support of metacognition components

This category is related to the support of metamemory, metacomprehension and selfregulation in metacognitive models.

2.1.3 Fundaments of the architectures

The category is related to the theoretical bases on which the metacognitive models are designed.

2.1.4 Computational implementations

This category alludes to the computational techniques used for the implementation of IS based on metacognitive models.

2.1.5 Terminology

This refers to metacognition terminology that is used in metacognitive models.

2.2. Identification of models, frameworks and architectures of metacognition in artificial systems

As a result of the review of this literature, a series of models are described that have been referenced in the development of IS with metacognitive abilities.

2.2.1 Theoretical framework for the operation of human memory [8]

A first important contribution in this area was the Theoretical Framework for the Operation of Human Memory [8], see Figure 1, which introduced the three principle keys for metacognition: Cognitive processes can be divided into several levels. The metalevel contains a dynamic model of the objectlevel. There are two dominant relationships called control and monitoring.

Today, the twotier architecture is the basis for the architectural design of metacognition in IS. See Figure 1.

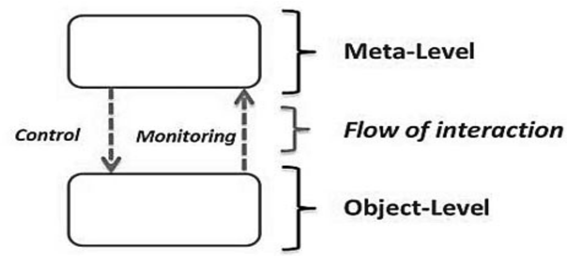

Figure 1. Metacognitive loop [8]

2.2.2 MetaAQUA [9,10]

Is a model based on the theory of Introspective Multistrategy Learning (IML) [10] and a cognitive model of introspection. The main functionality of the MetaAQUA system is the "story understanding", which is considered to be the base level in a MultiAgent System (MAS) [11]. The metalevel is structured by the implementation of IML [10], which in turn uses Case Based Reasoning (CBR) [12]. The learning strategy in MetaAQUA is implemented using a model of goaldriven learning (GDL) [13] and produces structures called metaexplanations.

2.2.3 CLARION theoretical framework [14]

Clarion theoretical framework is an overall architecture of the mind [14]. The architecture is used to construct models of specific metacognitive processes such as selfmonitoring and selfregulation (of cognitive processes). Clarion is used to capture experimental data related to metacognition with humans.

2.2.4 The MetaCognitive Loop (MCL) [15,16]

This is an architecture focused on detection of anomalies in learning processes and how to respond to them. MCL presents a general architecture and has three sets of ontologies [17], which are: ontology for anomaly types, failure ontology for use in assessment, and response ontology for selecting repair types to guide.

2.2.5 Simple model for metareasoning [18]

Cox and Raja [18] proposed a simple model for metareasoning. This model presents a double cycle of reasoning. The first cycle, refers to the traditional conception of cognitive science and AI about the reasoning in IS. Where an intelligent agent [11] receives perceptions of the environment, with which it makes decisions (reasoning), and acts, making changes to the environment. On the other hand, the second cycle of the simple model refers to the perception that the metalevel has about the objectlevel. The metalevel receives information from the objectlevel and make decisions (metareasoning).

2.2.6 EMONE Architecture [19]

EMONE is a cognitive architecture whose purpose is to support the kinds of commonsense thinking that is required to produce a possible scenario in a system. "Mental critics" [19] are used as a mechanism of operation in this architecture, these are procedures that recognize problems in the current situation. The Mental critics use commonsense narratives to suggest courses of action, ways to deliberate about the circumstances and consequences of those actions. Also, they can propose ways to reflect upon their mistakes when things go wrong. In EMONE there are mental critics for answering problems in the world, and other mental critics for answering the problems in the EMONE system itself.

2.2.7 Distributed metacognition Framework [20,21]

This is a conceptual architecture for distributed metacognition with contextawareness and diversity. A distributed metacognitive architecture is one in which all metalevel reasoning components can be monitored and controlled by other components of metalevel [20,21].

2.2.8 A metacognitive integrated dualcycle architecture (MIDCA) [22]

MIDCA is a novel architecture that incorporates both a perceptionaction cognitive cycle and a monitorcontrol metacognitive cycle [22]. In the metalevel the agent recognizes the problem, explains what causes the problem, and generates a new goal to remove the cause [9]. The metalevel reasoner can change the goals, the processes, and the input. MIDCA is based on the previous work by Norman [23], who designed a cognitive architecture.

2.2.9 Metalevel control agent architecture (Framework) [11]

The architecture is centered on how to make effective metalevel control decisions and has been implemented in MAS. This architecture is one of the precursors to distributed metacognition. The metalevel control uses an abstract representation of the agent state. The decisionmaking process is supported by decision trees.

2.3 Comparison between models

A comparison table (Table 1) is shown below as a source of information to supplement the description of the metacognitive models.

Table 1. Comparison between models

Model	Focus	Learning	Core	Techniques	Implementation
MetaAQUA [9,10]	The main functionality of the MetaAQUA system is story understanding	Goaldriven learning (GDL) Introspective Learning (IL)	Introspective Multistrategy Learning (IML)	Introspection	To retrieve from a CBR of introspective metaexplanations
CLARION Architecture [14]	Simulations of metacognitive monitoring and control/regulation	Reinforcement Learning (RL) QLearning	Implicit Decision Networks – (IDN)	Reinforcement Backpropagation	Multilayer Neural Networks
The MetaCognitive Loop MCL [15,16]	Detection of anomalies in learning processes and how to respond to them	Noteassess guide cycle Reinforcement Learning (RL) QLearning	Basic strategy of self-guided learning Decision making	Reinforcement	Ontologies Bayesian Networks
Simple model for metareasoning [18]	Introspective monitoring of reasoning about performance	*Not presents evidence*	*Not presents evidence*	*Not presents evidence*	*Not presents evidence*

EMONE Architecture [19]	To support the kinds of commonsense thinking required to produce a described scenario	Problem solving based on experience	Mental critics error-driven adaptive systems	Similarity measures Problem solving	CBR Common Lisp environment
Metalevel control Agent architecture MLCAA [11]	How to make effective metalevel control decisions	Reinforcement Learning (RL)	Decision making self-guided learning	Reinforcement	Decision trees Markov decision process MAS
Distributed metacognition Framework **DMF** [20 ,21]	Distributed metacognition with context-awareness and diversity	Cooperative learning	Diagnosis of a problem needs context-awareness	Social context awareness	Ontologies MAS
A Metacognitive integrated dualcycle architecture MIDCA [22]	Selfregulated learning with Introspective monitoring and metalevelcontrol	Introspective Learning	Introspective monitoring and metalevel-control	*No evidence*	*No evidence*

In Table 1 five main issues are presented which are used as the basis for the analysis of metacognition models, these are: The main focus of the model, Learning strategy used, Theory or approach on which the model is based, Strategy on which the model is based, and Computational technology used for the implementation.

2.4. Organization of terminology

The terms related to metacognition were organized into an ontology, due to the large number of terms related to metacognition that appear in the metacognitive models, and the semantic ambiguities of these terms among different models. The ontology was developed using Protégé 3.4 [24].

The objectives that guide the construction of the ontology are: a) to organize the terms and concepts that allude to metacognitive skills and clarify their characteristics and semantic relationships, b) to develop a generic and reusable semanticmodel based on ontology that includes the necessary features to provide clarity about metacognition concepts.

2.4.1 Methodology for ontology construction. The methodology of Noy and McGuinness [17] was followed to construct the ontology

The range of the ontology domain is supported by the following questions: What are the terms and concepts related to metacognition? What is the class and subclass hierarchy that makes the organization of terms and concepts related to metacognition possible? What are the main relationships among metacognitive skills? What relationships are necessary in the ontology to generate recommendations of actions, which can be used to design strategies for metacognitive skills scaffolding?

No ontology was reused, because no ontologies related to metacognitive capabilities in IS were found. Beneath, the elements and terms taken from metacognitive models are described. See Table 2.

Table 2. Support of Metacognitive Components

METACOGNITION RELATED TERMS
1].Goal-Setting
[2].Help seeking
[3].Introspection
[4].Metacognitive Skills
[5].Metacognitive Task
[6].Meta-comprehension
[7].Metaknowledge
[8].Meta-level control
[9].Metamemory
[10].Reinforcement Learning
[11].Self-Assessment (SA)
[12].Self-awareness
[13].Self-controlling
[14].Self-control
[15].Self-explanation (effect)
[16].Self-Help
[17].Self-evaluation
[18].Self-improvement
[19].Self-instruction
[20].Self-Monitoring (of cognitive process)
[21].Self-planning.
[22].Self-reinforcement
[23].Self-reflection (SR)
[24].Self-regulated learning (SRL)

For each category of metacognitive skill, class hierarchies were identified. For SelfRegulation a class hierarchy composed by SelfReinforcement, SelfInstruction and SelfControlling was built (Figure 2).

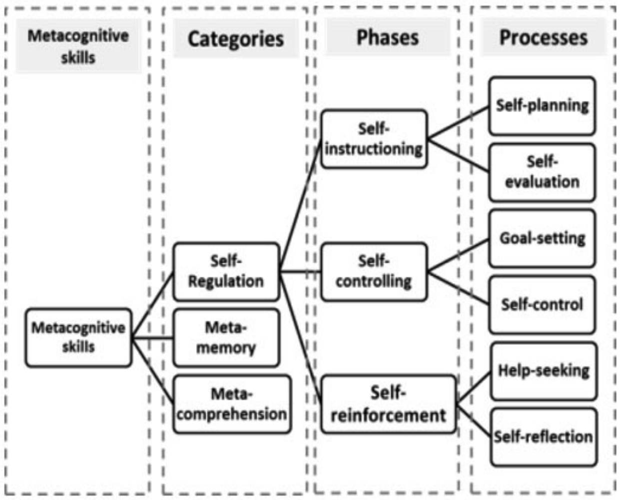

Figure 2. Selfregulation components

Regarding metamemory, the taxonomy consists in the classes and subclasses associated with control and metacognitive judgments (Figure 3).

The reasoning core for metacognitive skills, is formed by the relationships between instances of classes and a series of statements, which structure the semantics of the process. The properties that relate instances of different classes in the ontology are exposed in Figure 4.

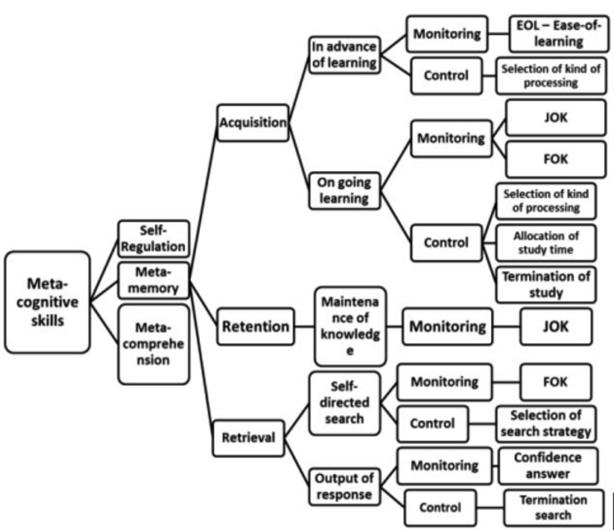

Figure 3. Metamemory components

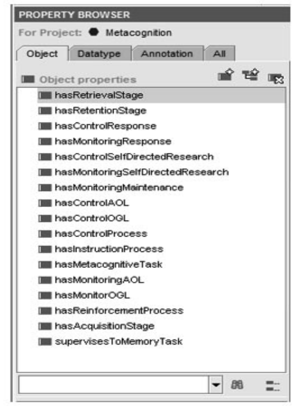

Figure 4. Classes for metacognition (Protegé)

3. RESULTS AND DISCUSSION

The results and discussion were organized according to the categories of analysis.

3.1 Types of metacognitive architectures

In metacognition models, two predominant types of architectures were found, which are: (1) Centralized architectures such as MetaAQUA, CLARION and MCL, which are predominant and are formed by a single metalevel that controls the entire metacognitive activity of the system. (2) The decentralized or distributed architectures such as MLCAA and DMF are composed of many metalevels. These kinds of architectures are managed by agents, using complex policies for communication and negotiation.

3.2 Support for metacognitive components

With reference to the support of the main components of metacognition: metamemory, metacomprehension and selfregulation, the majority of the architectures do not provide support for all three, see Table 3.

In relation to metamemory, it can be seen in Table 3, that MetaAQUA has a complex multifaceted memory [9,18] and reasons about memory events. While, in MCL aspects referring to metamemory strategies that can be used to learn from detected failures are left out [22]. Moreover, MCL has only basic mechanisms of shortterm memory, which in the metalevel are matched with longterm memory. EMONE implements a metamemory strategy based on a CBR system. MIDCA has a memory mechanism that can be accessed from the objectlevel and the metalevel. The rest of the architectures do not present clear support to control and monitor the memory process.

Table 3. Support of metacognitive components

MODEL	META-MEMORY	META-COMPREHENSION	SELF-REGULATION
META-AQUA [9] [10]	Memory awareness	Story understanding – meta-xps (meta-explanation)	Story understanding
Clarion Architecture [14]	-	-	Meta-level can act as an executive function
Meta-Cognitive Loop MCL [15] [16]	Basic mechanisms of short-term memory	Basic comprehension of object-level process	Anomaly detection – monitoring and control
Simple Model for Meta-Reasoning [18]	*No evidence*	*No evidence*	Introspective Monitoring
EM-ONE Architecture [19]	Metamemory based on cbr	Mental critics that use commonsense narratives	Commonsense thinking
Meta-Level Control Agent Architecture MLCAA [11]	*No evidence*	*No evidence*	Effective meta-level control decisions
Distributed Metacognition Framework DMF [20] [21]	Distributed memory system	*No evidence*	Context-awareness and diversity
A Metacognitive Integrated DUAL-Cycle Architecture MIDCA [22]	Memory mechanism which can access both the object-level and the meta-level	Explanation object-level	Introspective monitoring and meta-level control

Regarding metacomprehension, MetaAQUA, EMONE and MIDCA are the architectures that offer adequate support. MetaAQUA uses introspection [3,18] to represent reasoning traces with metaexplanation. EMONE has a strategy known as mental critics [19] that use commonsense narratives to suggest courses of action to deliberate about the circumstances and consequences of those actions.

In respect to Selfregulation, it can be clearly appreciated that all architectures provide full support for this component of metacognition. In MIDCA the metalevel can act as an executive function in a similar manner to CLARION. CLARION and MCL have better developed metacognitive processes than the rest of the architectures. Note that MetaAQUA, EMONE and MIDCA, are the most complete metacognitive architectures, because they provide support to three main components of metacognition: metamemory, metacomprehension and selfregulation.

3.3 Core of architectures

The metacognitive architectures are founded on learning strategies. These are: Introspective Learning (IL) [3,10,12,18], Reinforcement Learning (RL) [3,11,14,25], Learning by Experience (LE) [3,12] and Cooperative Learning (CL) [11,12]. See Figure 5.

Figure 5. Learning strategies in metacognition models

In computation, IL consists of the selfexamination or rational selfobservation of system reasoning state [3,10,26]. RL refers to the problem faced by an agent that learns some behavior through trialanderror interactions with a dynamic environment [25]. LE is a learning technique used in IS, that is based on the solution to new problems by adapting solutions to known problems [12,18]. CL is a learning technique used in MAS, which is based on communications policies and collaborative work [11].

MetaAQUA, MCL and EMONE are focused on responding to failures, but the first is based on Goaldriven learning (GDL), which is focused on IL. Second is founded on the NoteAssessGuide (NAG) [1] cycle, that is based on RL and the third uses LE because it uses errordriven adaptive systems with the purpose of finding solutions to presented problems.

CLARION, MLCAA, MIDCA and Simple Model for Metareasoning are focused on metacognitive monitoring [11,14,15], but CLARION and MLCAA implement decision making strategies for metalevel control, however, Simple Model for metaReasoning differs in the last aspect. EMONE and MetaAQUA share commons features, both have very complete support for problem solving and implement LE based on CBR systems. Moreover, CL is the base of MLCAA and DFM, both are architectures based on social context awareness and problem diagnosis in MAS.

CLARION and MetaAQUA are the architectures that implement more aspects related to learning approaches refering to metacognition.

3.4 Computational implementations

Continuing with the discussion, the computational aspects used for implementing IS [33] based on metacognitive architectures are listed in this paragraph. RL is the preferred strategy used by authors to implement learning capabilities in IS [11,14,15]. Moreover, RL is used in CLARION with Qlearning [27] and is implemented using backpropagation networks [28], see Table 4. While, in MCL, RL is implemented using Bayesian Networks (BN) [29].

Table 4. Learning implementation

LEARNING	IMPLEMENTATION
INTROSPECTIVE LEARNING IL	CBR
	KN
	GOALDRIVEN
	RULES
REINFORCEMENT LEARNING RL	QLEARNING
	BAYESIAN NETWORKS
	ONTOLOGIES
	MULTILAYER NEURAL NETWORKS
COOPERATIVE LEARNING CL	MAS
	MARKOV DECISION PROCESS
	DECISION TREES
	ONTOLOGIES
LEARNING BY EXPERIENCE LE	CBR
	SIMILARITY MEASURES

MLCAA implements SL following a decision making strategy denominated selfguided learning, which uses a Markov decision process (MDP) [11] over decision trees. All implementations of RL described above were developed using QLearning algorithms [11,1416].

Another computational technique implemented is CBR [3,12, 18]. CBR is a computational strategy for solving problems based on experience [30,12]. In metacognitive architectures, CBR is used to manage system memory and support the metamemory capabilities of IS [12,18]. In MetaAQUA, CBR supports both metamemory and metacomprehension, due to introspective metaexplanations [9]. While, in EMONE [19] CBRbased similarity measure, with an implementation of Common LISP Environment, is used.

MIDCA and Simple Model for Metareasoning do not present details of their implementation, they are in the design phase.

RL implementations based on QLearning is the most common support to selfregulation in metacognitive architectures. While metamemory and metacomprehension are implemented using strategies based on CBR.

3.5 Metacognitive ontology

Semantic description of terms related to metacognition is performed using the ontology created. Figure 6 shows the complete ontology.

In this section a list with definitions of the characteristics (facets) of the semantic relationship between the terms referring to metacognition is shown (See Table 5).

The specification of semantic relationships can contribute to provide clarity in relation to metacognitive concepts.

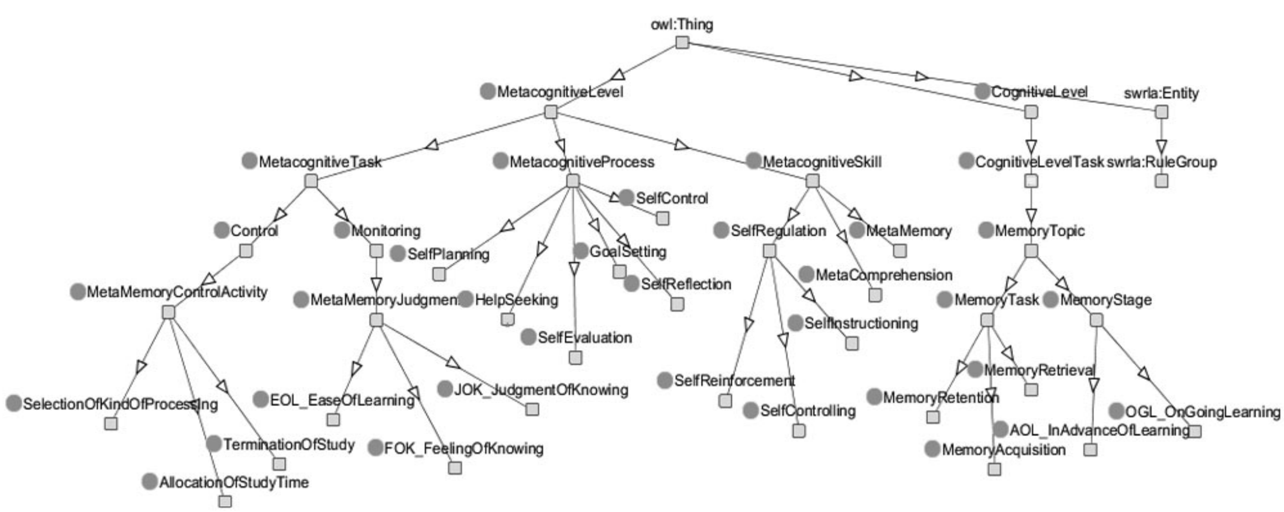

Figure 6. Representation of the Ontology using the Jambalaya plugin Protégé (elaborated by the authors)

Table 5. Semantic relationship

Semantic relationships	
Metacognitive Process	
Relationship	**Range**
hasSubClass	Selfevaluation
hasSubClass	Selfplanning
hasSubClass	Goalsetting
hasSubClass	Selfcontrol
hasSubClass	Helpseeking
Selfregulation	
Relationship	**Range**
hasSubClass	Selfreflection
hasSubClass	Selfinstructioning
hasSubClass	Selfcontrolling
hasSubClass	Selfreinforcement
Selfinstructioning	
Relationship	**Range**
hasSelfInstructionProcess	Selfplanning
hasSelfInstructionProcess	Selfevaluation
MemoryAcquisition	
Relationship	**Range**
hasAcquisitionStage	AOL_InAdvanceOfLearning
hasAcquisitionStage	OGL_OnGoingOfLearning
AOL_InAdvanceOfLearning	
Relationship	**Range**
hasControlAOL	SelectionOfKindOfProcess
hasMonitoringAOL	EOL_EaseOfLearning
OGL_OnGoingOfLearning	
Relationship	**Range**
hasControlOGL	TerminationOfStudy
hasControlOGL	SelectionOfKindOfProcess
hasControlOGL	AllocationOfStudyTime
hasMonitoringOGL	FOK_FeelingOfKnowledge
hasMonitoringOGL	JOK_JudgmentOfKnowledge
SelfControlling	
Relationship	**Range**
hasControlProcess	Goalsetting
hasControlProcess	Selfcontrol
SelfReinforcement	
Relationship	**Range**
hasReinforcementProcess	Helpseeking
hasReinforcementProcess	Selfreflection
MemoryRetention	
Relationship	**Range**
hasRetentionStage	MaintenanceOfKnowledge
MemoryRetrieval	
Relationship	**Range**
hasRetrievalStage	SelfRedirectedResearch
	OutputOfResponse
Metamemory	
Relationship	**Range**
SupervicesToMemoryTask	MemoryTask

4. CONCLUSIONS

In this paper we presented a research work based on four categories of study where it was found that there are two predominant types of architectures of metacognition in IS, centralized and decentralized.

The learning strategies present in metacognitive architectures are: Introspective Learning (IL), Reinforcement Learning (RL), Learning by Experience (LE) and Cooperative Learning (CL).

The most used computational implementation to support selfregulation in metacognitive architectures are RL implementations based on QLearning. While metamemory and metacomprehension are implemented using strategies based on CBR. CLARION and MetaAQUA are the architectures that implement most aspects related to the different learning approaches of metacognition

MetaAQUA, EMONE and MIDCA, are the most complete metacognitive architectures as they provide support for the three main components of metacognition.

An ontologybased semantic model was proposed which is composed of the terms and concepts found in the studied architectures.

Finally, the specification of semantic relationships among terms and concepts can contribute to provide clarity about understanding metacognition.

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