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How People Interact with Technology based on Natural and Artificial Intelligence

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A R T I C L E   I N F O

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A B S T R A C T

This paper aims to analyse the different forms of intelligence within organizations in a systemic and inclusive vision, in order to design an integrated environment based on Artificial Intelligence (AI) and Collective Intelligence (CI). This way we effectively shift the classical approaches of connecting people with people using *collaboration tools* (which allow people to work together, such as videoconferencing or email, groupware in virtual space, forums, workflow), of connecting people with a series of *content management* knowledge (taxonomies and documents classification, ontologies or thesauri, search engines, portals), to the current approaches of connecting people on the *use (automatic) of operational knowledge to solve problems and make decisions based on intellectual cooperation.* Few technologies have the big potential to review how we live, move, and work. Artificial intelligence (AI) is nowdays equivalent of electricity and the Internet. AI is expected to bring massive shifts in how people perceive and interact with technology, with machines performing a wider range of tasks, in many cases doing a better job than humans.

1. Introduction

AI is at the heart of today's technical innovation. AI is a new factor of production, driving growth by providing intelligent automation and potential labor augmentation [2,43]. Unlike traditional automation solutions, AI can help automate complex physical and reasoning tasks that require adaptability and self-learning; enabling workers to transition to more creative and innovative responsibilities. Intelligent systems are usefull in every field such as computer science, engineering, healthcare, management, aviation, etc. Researchers are interested to see intelligent machines which can to some extent mimic the human behavior. A number of techniques are reported in the literature to fuse intelligence in machines. These include Knowledge-Based Systems, Neural Networks, Fuzzy Systems, Evolutionary Systems, Intelligent Agents, fusion of intelligent paradigms, and so on [26,31,35,37]. Knowledge-Based Systems (KBS) also called expert systems were successfully used for performing tasks such as diagnosis, design, planning and so on. However, KBS are not very popular due to their inability to learn similar to humans. Neural Networks attempt to mimic biological problem solving mechanism that can learn, by itself, to solve a problem through a process of training. Neural networks are successfully used in many applications due to their ability to generalize. It means that neural networks usually come up with sensible solutions to problems for which they have not seen examples in training. Evolutionary systems use genetic selection of the biological world in solving problems. A number of variations of ES are proposed by researchers to apply it widely in a number of areas. AI is a long term technology that are inspired by biological systems, giving computers human-like abilities related to seeing, reasoning, hearing, and learning. AI market indicates that the technology is already deeply embedded in our lives, and its capabilities are growing at an exponential rate [3,6,10,12,13]. The *problem we formulate now* refers to the existence of a method to structure various forms of intelligence into a unified intelligence framework within the organization, based on **UIF** operational knowledge, with solid semantic interpretations and practical applications, the unifying element being the operational knowledge. Reformulated, the problem suggests the definition of the links between different types of intelligence, for understanding the relationship between them and secondly, to clarify the role and place of Knowledge Management (KM) in the synthesis of intelligent systems with applications in economy. Solving this problem, in the context of the present work, is an important step to achieve the objective outlined before, namely to develop a conceptual framework based on which can be developed intelligent systems rooted in KM. It is proven that change management, the culture and individual transformations, are, among other, important components that lead to changes that enhance organizational intelligence. From any perspective we look at the organizational structure, there is ever obvious the existence of various types of intelligence, which contribute to defining it as an intelligent

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organization, such as AI, Business Intelligence (BI), Competitive Intelligence (CI), Collective Intelligence (Collective Relationships Intelligence - CRI), Strategic Intelligence (SI), emotional intelligence, etc. The best way to use collective intelligence is based on knowledge mobilization and semantic technologies. We must not let computers to imitate people but to support people think and develop their ideas within a group. Collective intelligence helps people to think together, while AI tries to support people so as to limit human error. Within an organization, to manage collective intelligence is to combine all instruments (in this case semantic technologies), knowledge mobilization methods for developing KM strategies, and the processes that promote connection and collaboration between individual minds in order to achieve collective objectives, to perform a task or to solve increasingly complex problems [4,5,7,8]. In section 2 are considered the conceptual relations between different types of intelligence. Thus, we define an unified intelligence environment within the organization, based on operational knowledge (often inaccurate), called **UIF** (Unified Intelligent Framework), the conceptual basis of Intelligent Systems in Economy (ISE). In section3 we present the contribution of semantic technologies in supporting ISE development, future technologies that allow people and computers to create, discover, represent, organize, process, manage, reason, display, distribute and use imprecise meanings and knowledge to meet various business, personal or social goals [17,18,1927]. Operational knowledge or domain knowledge are of great interest in developing intelligent KMS and related practices, and are based specifically on individual competencies, on the experience gained by workers using knowledge, in a skilful way, in their daily work. We refer the current challenges of AI for economics. Section 4 is short and points out conclusions and the future impact of AI in our everyday life and business.

2. The role of AI in the development of KMSs with problem solving capacities

AI seeks to enable computers to achieve all what people can do, however narrowly regarding certain well defined specific areas of human activity [2]. AI is an important subject because of its ability to address new classes of problems, such as: perception, decision making, planning, diagnosis, signals interpretation, natural language understanding, and conception. These issues cover the gamut of human activities and have common features that rely fundamentally on the "intelligent" exploitation of large amounts of domain-specific knowledge. Typical applications in this field are the expert systems or the knowledge-based systems, ranging from single agent systems to multi agent systems. Also very important are the case-based reasoning systems, robotics, artificial view, neural networks, genetic algorithms, hybrid intelligent systems. AI occupies the central position in our definition for UIF. We may note that not all approaches to KM, CI, BI, CRI and SI must necessarily base on AI. Since AI has as fundamental goal the understanding and modelling of reasoning, it is natural that KM should be based, in some ways, on a series of AI concepts and techniques to help people capture, organize, and share knowledge within (with the stakeholders) and outside the organization [15,16,34.38].

AI techniques are the bases of current and future semantic technologies and can be used successfully in the analysis of knowledge flows within the various social networks or electronic institutions, distributed systems, communities of practice, intelligent enterprises, in modelling the dynamics of business processes, in virtual enterprises, and many other effective applications. In a brief review of the publications that cover AI topics, becomes visible that it is a set of subjects covering very different topics, from formal logics to automatic learning. In this context, seem surprising at first sight the terms that refer to a new AI [11,42]. Of course, in order to justify the new terms, we must briefly characterize the classical sense of AI.

Classical AI states that such systems should be based on knowledge. Consequently, they must possess a structure for knowledge representation and a mechanism for generating new knowledge (in terms of a desired behaviour). This knowledge is partitioned into small and understandable units that work together according to some methods that can be linguistically described to lead to the desired results [1,9,14]. In extenso, the method consists of problem analysis and system's synthesis through necessarily restrictive structures. The term most used for such a structure is the *rule,* used for both analysis and for the constructive description of the solution. The rule itself is stated based on *symbols*. Other structures related to this approach are frameworks, semantic networks etc.

Intelligence refers to the ability to rationally acquire and implement knowledge in different economic systems, business or decision making processes [33,36,41]. Starting from this brief definition of intelligence, were developed KM systems incorporating different and varied problem-solving skills. Knowledge-Based Symbolic Systems (KBSS) belong to this domain and are based on AI, aiming to formalize intelligent action. A rigorous definition of KBSS is mainly based on a series of logical foundations [33]. Logics is a discipline that grew out of reasons and with different objectives from those specific to AI. Mathematical logics was established at the beginning of last century in response to a series of fundamental problems in mathematics, the initial focus being the research of the concept of calculability and demonstration.

The basic idea of logics is to study the reasoning in various theories, which is why KBSS is based on these formalisms. In order to be used in a KBSS, knowledge is stored in the form of knowledge pieces that describe objects, facts, phenomena, processes and events in the *field of competence* of KBSS. All stored knowledge compose a *world model*, to which the system has access through organizing, classification, searching and recognition procedures. All these components, knowledge pieces and knowledge access procedures form what we call a cognitive system [30,40].

Logics' contribution to building KBSS is characterized in [31]: (1) *in theory,* logics contribute with a number of design elements and methods of the trilogy- type syntax / semantics / decision, inference, coherence (knowledge base coherence checking, truth maintenance systems), decidability (i.e. by default logic is not semi-decidable, contrary to first-order logic, some temporal logics are decidable, others not), the complexity of decision-making methods. The logic is thus a benchmark for the substantiation of AI systems. (2) *formalizing various types of reasoning*. Logics has a normative role even in the absence of reliable knowledge. Automatic demonstration, knowledge representation languages, logic programming languages, are all means which support and integrate reasoning methods. The logic used to describe and design a KBSS is not exactly the one that is directly applicable in terms of classical mathematical foundations. Mathematical logic is characterized trough a rough classification, which does not distinguish between two representations of same object, while KBSS is strictly sensitive to the different ways of representation, especially in the presence of uncertain and imprecise characteristics.

Intensional semantics is used to capture the important aspects of this phenomenon. While practitioners and researchers continue their efforts to design and build complex systems, it was realized that uncertainty is present not only in human knowledge. Allowing a certain degree of uncertainty in describing complex systems, is perhaps the most significant way to simplify them. Different types of imprecision can be rigorously characterized and investigated in the context of fuzzy sets theory. Thus, the ability to operate in an uncertain economic environment, imprecise or partially known, as is the case for most companies, is one of the basic performance of any AIS system embedded in a KMS. These systems must be designed as multi-agent systems, with the possibility to combine different knowledge-based techniques (with the purpose of acquiring and processing information), with approximate reasoning methods. This will allow KBSs to better emulate human decision-making process, characterized by inadequate, imprecise and time-variable knowledge. Real-time calculation is an area of intense research, whereas the accuracy of KBSS operation in a dynamic and distributed environment depends not only on its developing logic, but also on the temporal aspects involved (the case of real time operating enterprise - RTE). Such systems are subject to various complex time restrictions, with various levels of granularity of the time. Temporal knowledge is a key issue for a large number of applications (real-time planning, business processes administration and management, and dynamic situations management). A KBSS must have reasoning capacities to consider a series of events that can occur: interruptions, processing time limitations, synchronous or asynchronous nature of the occurrence of new events.

Considering the time must highlight two complementary aspects: temporal information management and formalizing the reasoning methods over time and in real time. Some approaches are based on numerical models, and other on symbolic representations of the time. Reasoning under real-time restrictions has specific characteristics: real-time operation often involves temporal reasoning. Neural intelligence of knowledge is essential for the sixth generation and it is much broader than knowledge engineering, including advanced reasoning techniques, adaptive, real-time, symbolic and fuzzy reasoning, based on a comprehensive knowledge synthesis, massively parallel. Its features include among others: natural user interfaces based on unrestricted dialogues, through language and image; brain waves and neural signals interfaces; quasi-human behaviours providing the user with very intense and complex sensations; environment interface through very precise sensors, their data allowing self-organization, adaptation and learning; automatic programming (e.g. genetic programming). AI systems generally have the following characteristics: performing operations in hostile environments, large and broad knowledge areas, ability to interact naturally with humans and a certain degree of adaptation and internal integrity [14,32,39]. From this perspective, we emphasize: (1) *The economic environment cannot be predicted*. For an intelligent agent, faced with demands that change over time, is vital to learn quickly from experience and adapt to environmental changes in order not to fail. (2) *The system requires large amounts of knowledge about the economic environment.* It must include this information in a suitable form to be used in various tasks, in order to achieve performance and to acquire information from its own experience of solving problems through cooperation with people or with other agents. Exploring large chunks of poorly structured information, such as WWW, requires dexterity and efficiency in handling large quantities of complex information. (3) *To interact with human collaborators, the system must engage in extensive dialogues* to progressively clarify and enrich knowledge deepness. This requires the use of natural language, appropriate displays and tactile communication methods, unlike the simple exchange of correct sentences required by nowadays' limited systems. Interaction with their artificial collaborators leads to economy and clarity, and does not compulsorily require the use of the same language to communicate with people. (4) *The system must understand itself* in the same way that his collaborators understand it, as it better integrates its various components, facilitates their smooth interaction, maintains and enriches their knowledge and skill, and dynamically adjusts the resource usage.

3. Current challenges for AI in economics

Building economic intelligent systems with such characteristics is challenging for AI and for each area of exploration: knowledge representation and processing, learning and adaptation, debate, planning and action, language and speech processing, image understanding and synthesis, manoeuvring and locomotion, autonomous agents and robots, multi agent systems, cognitive modelling, and mathematical foundations -

supports a rigorous research effort and contributes to meeting these challenges. These lines consist of systematic analysis and intellectual integration, including building robots (physically and computationally) and the rational modelling (mainly in terms of decision making) outline two special and comprehensive cases. To support collaboration, increase communication, obtain important knowledge required to act intelligently and to deepen the corresponding mathematical foundations are another major directions of AI. The idea of distribution is an innovative trend in AI, due to its reduced complexity by decomposing a problem, modularity, reliability. The concept of distributed AI relies heavily on at least three non-exclusive approaches: AI systems parallelization (parallel algorithms and machines), multi-agent systems or knowledge multi-bases, overall distribution of knowledge and reasoning. At this level, there are two important mechanisms: cooperation and competition. Distributed AI is a subfield of AI, researching methods of distributed knowledge bases synthesis, communication and reasoning techniques needed to participate in societies composed of people and computers. Distributed Artificial Intelligence (DAI) is concerned with situations in which a series of systems interact to solve a common problem. The objective of this discipline is to build a theoretical framework and tools for modelling agents with planning and communication skills. DAI area is bounded by two research domains: distributed problem solvers (DPS) and multi agent systems. DPS have as strategy, in solving large problems, their split into sub-problems until it is reached the tasks level, which are then assigned to agents (nodes and modules). The agents form a team in which the components cooperate in using the knowledge about the problem and in developing methods to obtain the solution. Cooperation and coordination are incorporated as functions into the system in the design phase (top-down). DAI considers that the component entities have intelligence, opposite to connectionist systems, where the individual components are combined to form an intelligent whole. This area does not address issues related to parallel or distributed processing, but deals with the coordination of concurrent processes at different levels of representation and resolution. As a result, DAI is not interested in parallel processing for AI for reasons of calculation efficiency. Efforts are directed towards solving the problems of efficiency of AI systems and towards the conceptual understanding of intelligent reasoning and behaviour of a variety of agents. In distributed artificial intelligence there are not addressed issues related to parallel computing architectures and parallel programming languages. Its scope includes approaches for structuring and organizing the research effort from: (1) the agent's perspective, bringing together those elements that characterize the agents involved in the multi agent system; (2) the group's perspective (refers to the elements that characterize the group of agents) can be approached in several ways: group organization, coordination, cooperation, negotiation, consistency of behaviour, planning, communication; (3) the perspective of specific approaches - relates to issues of open systems, reflection, autonomous agents and organizational information systems; (4) the designer's perspective - refers to implementation methods and techniques for building multi-agent systems, test standards and designing such applications.

Multi agent systems focus on the coordination of the behaviour of a set of autonomous agents, which in addition to their individual objectives, aim at solving a common problem (bottom-up). A multi agent system can be defined as a loosely coupled network of knowledge-based solvers, working together to solve a problem whose resolution exceeds the capacity of any individual participant. The individual problem solvers (called agents) are autonomous or heterogeneous (have different resolution capabilities), each possessing incomplete information. The fact that the resources (processing, storage and communication), expertise and information necessary to solve the problem have different locations, and the processing is asynchronous, requires cooperation. The evolution of the individuals is largely determined by their membership in communities. Collaborative activities in these communities lead to the development of the group and provide advantages to the individuals that make up the community. This social environment is analysed and simulated by multi-agent systems, studying the agent as part of the social space of other agents, and not only the physical world or an isolated agent. Social information includes information about values, strategies and intentions as well as information about the state of the world and is the basis for introducing the basic concepts for information social science and multi agent systems. Information is active through its participation in creating interactions between agents. Agents are entities that participate actively in the social space of interactions. One of the current concerns of AI is to develop software systems that deal with issues in the area of capabilities related to agent societies. Intelligent behaviour requires *coordination, communication and negotiation*. Coordination means adapting to the environment (in which an agent society operates) achieved by modifying agents' behaviour. The environment is support for communication and mediates the transfer of coordination information. Agents are autonomous problem solvers, with own objectives, intentions, capabilities and knowledge, that carry out their actions according to various plans. Plans are set of rational actions of the agents. Multi agent systems formal theories are specifications of the agents that provide a basis for designing, followed by their implementation and verification. Multi agent approaches represent a new direction, distinct from software engineering, that take into account complex distributed systems containing autonomous cooperating agent societies. Different approaches are related to: (1) *The high level provided by the current technology*. The high technological level reached in processing, memory and communication capacity enables asynchronous coupling of a large number of agents. Efficient explorations of these structures, theoretical and practical approaches are suitable when well-known techniques do not give satisfactory results. (2) *Inherent distribution*. Most AI applications are, by their nature, distributed. The use of multi-agent systems offers several advantages compared with single monolithic systems: speed (by exploiting parallelism), reducing traffic (by communicating partial results rather than raw data to a processing centre), increased flexibility (agents with different capabilities can quickly form teams to solve various kinds of problems, normally different) and increased reliability (through takeover, by other team members, of the failing agents' tasks). (3) *Epistemological reasons* (cognitive models of cooperation). Cooperation and coordination are complex phenomena. DAI can provide a better understanding of the interactions between people and of how they are organized in groups to solve problems.

For the creation of an intelligent agent, knowledge representation is a crucial issue. Like any other AI application, what an agent is expected to do and in what areas, will have a significant impact on the type of knowledge representation. If the agent has a limited number of situations to which must respond, then its intelligence may be due to procedural programs. Instead, if the agent has to build or to use sophisticated models of problem domain and to solve problems at different levels of abstraction, then it is necessary to use semantic networks. If the agent has to respond to questions or needs to generate new facts from existing data, then must be used predicate logic or if-then rules. If the agent will interact with other agents and must share knowledge, then it will probably have to read and write Knowledge Interchange Format (KIF) data type. In many applications are used multiple knowledge representations. If intelligent agents are a novelty for the software commercial environments, they aroused the researchers' attention for some time, and so were proposed several ways of classifying agents: by their classification in the context of intelligence, agentification and mobility; by focusing on the primary processing strategy of the agent; according to the functions they perform.

Cognitive agents contain an explicit symbolic representation of the world and are able to make decisions (what actions to execute) based on symbolic reasoning. They have set goals and are able to modify their actions in terms of environmental changes and of their interaction with other agents, in order to achieve these goals. Each cognitive agent is a knowledge-based system, with greater or lesser degree of resolution, and which includes all its associated methodology. In the case of cognitive agents systems, the system's intelligence is given both by the sum of each agent' individual intelligent behaviour and by the intelligence resulting from the collective behaviour based on social interaction. A cognitive agents system is, for example, an automatic planner for filling a meeting room belonging to a big company. The emergence of open systems and of decentralized distributed design required a new approach to distributed problem solving, i.e. *multi agent systems* (MAS). A multi agent system is a distributed system consisting of a collection of autonomous agents that interact within a common environment, each agent with own knowledge, action skills and goals. Most times, MAS are intelligent systems. We can identify two categories of intelligent multi-agent systems: cognitive agents MAS, also called cognitive multi agent systems, and reactive agents MAS, called reactive multi agent systems. *Cognitive multi agent systems* attempt to simulate aspects of human behaviour model by including the notions of goal, cooperation, competition and organization in social structures, and to establish the dependency relationships between these structures, the learning capacity and self-improvement. A cognitive multi-agent system can be seen as a particular knowledge-based system which contains a symbolic representation of knowledge about the world in which evolves and which is able to make decisions (e.g. what action to perform) via an inferential process (reasoning). Unlike a classic KBSS, an agent of a MAS describes symbolically the world both through beliefs, which are opinions about the world, possibly incomplete or misleading, and through knowledge, which are real facts.

Reactive multi agent systems are systems in which the agents are simple processing units, capable of reacting to environmental changes and, subsequently, of performing simple actions. The model is mainly inspired by the biological structure of insect communities: a bee cannot be considered intelligent, but the beehive's behaviour as a whole and even the organization of the bees certainly has elements of intelligence, executing joint and coordinated actions to achieve the goal. According to reactive MAS followers, real intelligence is located in the outside world and not at the individual processing components level, intelligent behaviour being a result of interaction between agents and environment, and intelligence an emergent property of the system as a whole.

The reasoning is a fundamental component of any intelligent system and especially of any system that will automate the knowledge-based work, as will do the future semantic technologies. Characteristics of reasoning, as shown by the own analysis and development of such systems, involve many aspects.

To each mode of knowledge representation corresponds one or more operating algorithms, also called reasoning algorithms: for example, in mathematical logic, the resolution principle. It should be noted that, in terms of informatics, reasoning algorithm is a procedural representation of the semantics attached to the knowledge with which it operates. From a practical perspective, the exploitation of a knowledge-based system is affected by a certain indeterminism, combinatorial explosion of solutions, which require the management and supervision of reasoning. There are two main approaches in this regard: **a)** data driven or bottom-up, **b)** guided by a goal (or more). Such a reasoning control is a metareasoning and corresponds to various fundamental cognitive processes. The set of reasoning processes must be supervised in complex applications by an overall strategy, capable of making decisions, according to the current situation. Mathematical logic is an excellent example. Two logical formalisms are used: propositional logic and first order predicate logic.

Developing advanced knowledge-based systems, needs elaborating mechanisms for approximate reasoning, for handling the imprecision and the inherent uncertainty. Treating these issues involves: defining the ways to represent uncertainty and imprecision, adapting the exploitation schemes, proliferating the "approximate" character during the reasoning process. Approaches to this issue are varied, but one theory about the symbolic nature of the reasoning remains to be developed. The idea of associating a degree of uncertainty to a logical formula is not new. A probabilistic logic was defined, and one of the first KBSS (PROSPECTOR) used Bayesian probabilistic approach. This formalism is less used compared to other more empirical or better adapted models, such as: possibility theory, Dempster-Shafer theory, etc. Approximate reasoning is very important, as it is the basic element in other types of reasoning.

Time is an important and original dimension of knowledge based systems. There are multiple aspects. Temporal evolution of the universe of an application requires updating the truth value at different moments. The idea of revising the reasoning is central. Temporal reasoning allows reasoning in the past and future. Real-time introduces an operating restriction specific to reasoning mechanisms. Real-time reasoning involves a temporal reasoning, but the reciprocal is not always true. Reasoning "over time", enables a multitude of functions of great importance in a real KM application: considering the temporal links between events, reasoning about events that will occur, maintaining a set of temporal and evolutionary facts and knowledge, planning the actions and managing their subsequent effects. Temporal reasoning is an active area in artificial intelligence research undertaken to achieve the intelligent enterprise, through applications of great practical interest: planning, understanding the written or oral language, interpretation of situations, business process management. Considering time in reasoning mechanisms first requires a proper representation of the problem. There are many possible representations, some of which are purely numeric (differential equations), but which will be (at least for now!) excluded because they do not allow explicit reasoning. We are interested in representations that essentially appeal to a symbolic formalism (without neglecting the numerical aspect, always present). All these formalisms are extensions of logic: modal logic, with modal temporal operators that allow manipulation of the past and the future, that associate a temporal component (interval or instance) or a temporal attribute with a timeless component. Temporal reasoning has serious connections with other aspects of reasoning: causality, action planning, hypothetical reasoning, etc. The idea of distribution is an innovative idea in KM, due to complexity reduction, by decomposing a problem, modularity, reliability. The concept of KM distributed systems relies heavily on at least three non-exclusive approaches: the parallelism of artificial intelligence systems (parallel algorithms and machines), multi-agent systems with knowledge multi bases, total distribution of knowledge and reasoning. At this level there are two important mechanisms: cooperation through negotiation and competition.

Planning and reasoning involve designing a set of actions (or plan) for achieving a goal. A plan may be for an assembly robot, a manufacturing workshop, or any KM system able to provide the expected result by following a plan. Planning is to infer on actions and plans, thus contributing to the development of important concepts (time, causality). The knowledge transfer from a particular knowledge source to a KBSS is called *knowledge acquisition*, and there are several sources from which they may come. Extracting knowledge from a human expert through specific means or through the method of interviews, is a heterogeneous process. Knowledge acquisition or knowledge engineering can be divided into the following five stages: **i)** *Identifying* the problem and determining its characteristics; **ii)** *Conceptualizing the problem*: determining the concepts that support the knowledge representation; **iii)** *Formalization*: choosing the knowledge representation methods and the inference mechanism; **iv)** *Implementation*: the actual knowledge representation of chosen formalism (rules, semantic networks, frameworks, etc.); **v)** *Testing*: knowledge verification and KBSS validation. The whole process is iterative. The test results may indicate the reformulation of the problem, redefining concepts, redesigning knowledge structures or refining the knowledge. Throughout this process, the knowledge engineer works along with the domain expert. Their balanced combination and management make a business thrive. Knowledge and information are essential and must be taken into account by the management of any enterprise, if it aims a successful and effective operation.

Classical AI states that such systems should be based on knowledge. Consequently, they must possess a structure for knowledge representation and a mechanism for generating new knowledge (or a desired behaviour). This knowledge is partitioned into small, understandable units which work together according to some methods that may be linguistically described, to achieve the desired results. In extenso, the method consists of problem analysis and system synthesis through necessarily restrictive structures. The term usually used for such structures is *rule*, used for both the analysis and the constructive description of the solution. The rule itself is stated based on *symbols*. Other structures related to this approach are the frameworks, semantic networks, etc. Criticism of this approach to AI relates in particular to the efforts of using such systems to explain human cognitive phenomena. In this context, the new trend in AI uses new methods (specific to neural networks) to model cognitive systems and, in the end, intelligent systems. The new features come from the ways of building the knowledge model, i.e. obtaining a model of complex behaviour that is difficult to simulate and predict, but which pursues some predefined objectives. It should be noted that the new trend in AI concerns with the cognitive modelling issue, having as sources biology and evolutionary theories, in the context of the hypothesis that human intelligence is historically based on that of the animals. Reducing problems (in the classic sense of AI) to a correct and complete set of rules is necessary because of real time conditions imposed by the use of von Neumann architecture. But this modelling by reduction also involves the reduction, in its actual substance, of the meaning of AI areas (automatic demonstration of theorems, natural language processing). All of these traditional disciplines tend to exclude the subject of their own investigations, by including the objectivity of mathematical, logical and language tool. The main characteristic of an AI problem is the explosion of combinations and the diversity of possible actions and solutions, as well as the diversity of inputs. This is a decisive cause for the need for a viable mechanism of reducing the complexity of the problem, aiming the modularization of cases diversity, the correct decision in each case and validation of the completeness (covering all cases).

Rules, in the context of using predicates, have a comprehensive role, aiming to reduce the problem complexity in terms of a particular objective, with the price of reducing the meanings, thus the diversity. On the contrary, the new meaning of AI aims a non-reductive treatment of as many aspects of human knowledge, with or without minimal predicative constraints on a model's input diversity (based on the premise that the designer cannot anticipate all the necessary aspects of modelling). The only remaining approach is *learning*, by reaffirming the history and subjectivity as the necessary conditions of the intelligent act. Thus, are emphasized the subject's experience and contextual qualities. One of the main problems of such an approach is to design and specify the objectives. Such an objective involves problems similar to designing a set of rules: the determination of reasonable goals is comparable in difficulty to establishing the correctness and completeness of the set of rules that describe the model's behaviour. One possible practical answer to this problem can be learning. The problem of correlating symbolic methods, based on rules, with associative processing, based on connectionism, should combine the advantages of both approaches. Results of neural-symbolic integration can be applied both to explain human cognitive processes (identification, association, generalization, reasoning, characterizing the different states of mind) and to build adaptive systems to recognize, classify, learn from examples, to self-organize, to reason, to use natural language.

In this context, neural networks (Artificial Neural Networks, ANN), regarded as a model of the human brain, can be interpreted, due to the approximations and simplifications used, as an opportunity of "high" level cognitive approach. Sub-symbolic cognitive processes that depend on the features of internal neural representations (some invisible for external world), are implemented through neural schemes and models. These characteristics may represent different data types: sensorial signals, numerical information, linguistic variables. There can be imagined a coordinate system based on these characteristics that defines the multidimensional mental space: in this space, a mental function is defined by describing the mental objects as fuzzy domains, in which the function has nonzero values. The active values of the internal representation at a time are given by the mental state, to whom corresponds a point in mental space. If in this region exists a mental object, it will be recognized (enabled). The evolution of mental states is equivalent to a sequence of object activations in the mental space. These objects are created and positioned using methods of learning, both supervised and by self-organizing. Associations between mental objects are based on the distance between them, considering not only the representations' properties but also the spatial-temporal correlations. In these circumstances, the intuition is dependent on the mental space topography. We thus get a dynamic evolution of the logical reasoning within the mental space (successive activation of mental objects). Logical reasoning and the one based on rules become thus an approximation of the mental states dynamics.

In a brief review of publications that cover AI topics, becomes clear that AI is a complex of disciplines, covering very different topics, from formal logic to automatic learning. AI is intended to create intelligent computers. AI seeks to enable computers to achieve all what people can do, however restrictive to specific well defined areas of human activity. Classical AI states that such systems should be based on knowledge. Consequently, they must possess a structure for knowledge representation and a mechanism for generating new knowledge (or a desired behaviour). New trend in AI uses new methods (specific to neural networks and genetic algorithms) to model cognitive systems and, ultimately, intelligent systems. The new features come from the ways of building the knowledge model, i.e. obtaining a model of complex behaviour that is difficult to simulate and predict, but which pursues some predefined objectives. It should be noted that the new trend in AI concerns with the cognitive modelling issue, having as sources biology and evolutionary theories, in the context of the hypothesis that human intelligence is historically based on that of the animals. Reducing problems (in the classic sense of AI) to a correct and complete set of rules is necessary because of realizability conditions imposed by the use of von Neumann architecture. But this modelling by reduction also involves the reduction, in its actual substance, of the meaning of AI areas (automatic demonstration of theorems, natural language processing). All of these traditional disciplines tend to exclude the subject of their own investigations, by including the objectivity of mathematical, logical and language tool. The main characteristic of an AI problem is the explosion of combinations and the diversity of possible actions and solutions, as well as the diversity of inputs. This is a decisive cause for the need for a viable mechanism of reducing the complexity of the problem, aiming the modularization of cases diversity, the correct decision in each case and validation of the completeness (covering all cases).

Rules, in the context of using predicates, have a comprehensive role, aiming to reduce the problem complexity in terms of a particular objective, with the price of reducing the meanings, thus the diversity. On the contrary, the new meaning of AI aims a non-reductive treatment of as many aspects of human knowledge, with or without minimal predicative constraints on a model's input diversity (based on the premise that the designer cannot anticipate all the necessary aspects of modelling). The only remaining approach is *learning*, by reaffirming the history and subjectivity as the necessary conditions of the intelligent act. Thus, are emphasized the subject's experience and contextual qualities. One of the main problems of such an approach is to design and specify the objectives. Such an objective involves problems similar to designing a set of rules: the determination of reasonable goals is comparable in difficulty to establishing the correctness and completeness of the set of rules that describe the model's behaviour. One possible answer to this problem can almost always be learning. The problem of correlating symbolic methods, based on rules, with associative processing, based on connectionism, should combine the advantages of both approaches. Results of neuro-symbolic integration can be applied both to explain human cognitive processes (identification, association, generalization and reasoning, characterizing the different states of mind) and to build adaptive systems to recognize, classify, learn from examples, to self-organize, to reason, to use natural language. In this context, ANN regarded as a model of the human brain, can be interpreted, due to the approximations and simplifications used, as an opportunity of "high" level cognitive approach. Sub-symbolic cognitive processes that depend on the features of internal neural representations (some invisible for external world), are implemented through neural schemes and models. These characteristics may represent different data types: sensorial signals, numerical information, linguistic variables. The active values of the internal representation at a time are given by the mental state, to whom corresponds a point in mental space. If in this region exists a mental object, it will be recognized (enabled). The evolution of mental states is equivalent to a sequence of activation of objects in mental space. These objects are created and positioned using methods of learning, both supervised and by self-organizing. Associations between mental objects are based on the distance between them, considering not only the representations' properties but also the spatial-temporal correlations.

4. Conclusions

KM is the next layer of the proposed structure for UIF, intimately connected to AI. Many organizations have accepted KM as a particularly important component in their human capital strategy [22,24,29]. An impressive number of researchers and practitioners have studied and created various techniques and methodologies for developing strategies based on *knowledge mobilization*, as well as various plans to implement these strategies, in the form of KM Systems of current and future generation. New generation systems must solve a series of *dilemmas* currently existing at the level of KM practices and systems, such as: the tension between distributed processing of knowledge-based tasks (in *groups of organizations*, *communities of practice*, *social networks*) and the technologies used [20,28], the serious issues related to the semantic of all knowledge in the real time creation and operating processes [21], a clearer definition and acceptance of the KM, as it is practiced within various organizations that are becoming increasingly complex (in the form of virtual organizations), accessing knowledge in various *strategic alliances*, a foremost process even before the knowledge acquisition [23,25]. Competitive Intelligence (CI) is the layer located between BI and CRI (Collective Intelligence) in the context UIF's framework. The more the Internet breaks a series of traditional barriers between enterprises' businesses, the more dramatically increases the competition for improving product development cycles and the company's profit is often unpredictable. CI can help any company to become an impressive competitor in a particular industry or on a specific market segment. CI is the set of procedures to analyse information in a continuous process. CI is not simply a set of methods for determining information about competitors. CI focuses on generating procedures (intelligent) to support a series of decisions that relate to future events. Clearly every company needs information about competitors, but needs, at least equally, to know (therefore information or knowledge) a number of issues about the industrial or business environment to which it relates. Strategic Intelligence (SI) is an aggregation of the aforementioned types of intelligence, being located on the layer that wraps (at least conceptually) this hierarchy of intelligent components. SI must provide value-added information and knowledge to support the organization in making the best decisions. SI is most often used in military or defence, to make high level decisions. SI is categorically different from operational or tactical intelligence, which are forms of low intelligence. In the economic field, SI has roughly the same connotations as in military, the difference relating to how to practically use it in this area. More specifically, the focus is on answering the question "how well can be set the organization to meet future challenges and opportunities, in order to maximize its success?" UIF intelligence unified framework aims to bring together different types of intelligence, starting with AI in the UIF core and continuing with KM, BI, CI, CRI. It is not necessary that KM should include AI, at least from the traditional managerial perspective of KM. It has been proven in the recent years and especially for the coming years, that distributed AI (by the outstanding achievements in this field, namely the great capacities to resolve very complex problems) has a huge potential in supporting the development of advanced KM systems, based on *semantic technologies*, much closer to the companies' needs in supporting various business processes. Successful manager needs more than native intelligence. Leaders and managers need a developed emotional intelligence. They interact with a large number of people and represent the organization in front of the public. Every time we make a choice we use our emotions. Collective intelligence is the intelligence of connections and relationships. Society is nowadays at a very important point in determining how to deploy AI-based technologies so that the relationships between people and machines will become more effective and useful in transportation, home robots, mobile healthcare, education, public security, employment and workplace, etc. AI has to be used in artificial systems for large-scale machine learning, deep learning, robotics, computer vision, natural language processing, collaborative systems, Internet of things, game theory and computational social choice, neuromorphic computing to improve hardware efficiency.

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