# Technology of mental functional representations as a first stage of conceptualization and implementation of complex scientific knowledge in innovation processes

## Технология ментальных и функциональных репрезентаций как первый этап концептуализации и реализации комплексных научных знаний в инновационных процессах

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*In innovation processes, it is common to deal with highly cross-multidisciplinary topics. For example, an innovation process may integrate psychological, neuroscientific, biological and engineering disciplines, among many others dealing with bio-cybernetic systems. One specific type of those theories is related to cognitive processes, knowledge representation and self-learning systems. Therefore, there is a need to easily and rapidly understand, as well as apply and share knowledge of complex theories by innovation managers, engineers, scholars, training practitioners, computational modelers, managers, and stakeholders, among others. In this regard, the present article provides with a graphical tool to represent complex cross-multidisciplinary theories, concepts and processes in a simple, concise, and logical manner, by using functional principles and graphical representations that have been successfully used in engineering and technology areas such as adaptive control systems, algorithmic flow charts, and computational cognitive neuroscience. Once described the models that have been typically used to represent and model knowledge and cognition, functional cognitive modeling is introduced, and then applied to represent and model complex cognitive theories from psychology and neuroscience such as Jean Piaget's Theory of Intellectual Growth, Antonio Damasio's Somatic Marker Hypothesis, and Dante Dorantes' Soft Skills Model.*

*В инновационных процессах часто встречаются с междисциплинарными темамы. Например, инновационный процесс может затрагивать в том числе психологические, нейролингвистические, биологические и инженерные дисциплины, связанные с биокибернетическими системами. Одна из рассматриваемых теорий связана с когнитивными процессами, представлением знаний и с системами самообучения. Менеджерам по инновациям, инженерам, ученым, специалистам по обучению, специалистам по моделированию и заинтересованным сторонам, необходимо легко и быстро понимать, применять, а также обмениваться знаниями по сложным теориям. В связи с этим, в настоящей статье представлен графический инструмент для представления сложных междисциплинарных теорий, концепций и процессов простым, лаконичным и логичным образом с использованием функциональных принципов и графических представлений, которые успешно использовались в инженерных и технологических областях, такие как: системы адаптивного управления, алгоритмические блок-схемы и вычислительная когнитивная нейробиология. После описания моделей, которые обычно используются для представления и моделирования знаний и познания, вводится функциональное когнитивное моделирование, а затем применяются для* *представления и моделирования сложных когнитивных теорий из психологии и нейробиологии, таких как теория интеллектуального роста Жана Пиаже, гипотеза соматического маркера Антонио Дамасио и модель мягких умений и навыков Данте Дорантеса.*

**Keywords**: cross-disciplinary, multidisciplinary, mental model, mental representation, functional model.

**Ключевые слова**: междисциплинарный, многодисциплинарный, ментальная модель, ментальная репрезентация, функциональная модель.

## 1. Introduction

This article mainly focuses on psychological, neuroscientific, biological and engineering disciplines, among others, dealing with bio-cybernetic systems for which cognitive processes, knowledge representation and self-learning mechanisms is a common characteristic. For this reason, we are not covering system modeling methods, which are more general forms of system representation that can be found elsewhere.

Cognitive Science has addressed modeling theories in disciplines ranging from neuroscience, psychology, biology, to artificial intelligence [1]. Reviewing these theories from different contexts, cognitive science has positioned itself as a common ground in which models of mental processes from multiple disciplines merge. To this regard, the authors have identified a need for more complete, graphic representations that incorporate developments in the field, and potentially make these theories more widely accessible for a wider audience.

One of the first contemporary mental representations was proposed by Johnson-Laird's reasoning models [2], since then, most advances have been focused on the topic of knowledge representation in the fields of artificial intelligence and cognitive informatics [3]. While graphical representation of mental models is needed for a better understanding of different theories, the analysis, evaluation and integration of the models usually do not deal with actual teaching and dissemination purposes across multidisciplinary fields. Hence, this article proposes a solution to graphically represent complex cross-multidisciplinary theories, concepts and processes in a simple, concise, and logical manner, by using functional principles and graphical representations that have been successfully used in technical areas such as adaptive control systems, algorithm flow diagrams, or computational cognitive neuroscience.

## 2. Cognitive Representation Models

Cognitive models and processes are formed by static components such as entities, categories, concepts, facts, etc., and dynamic components such as skills, habits, procedures, intentions, actions, speech, stimuli, attention, sensation, perception, memories, awareness, emotions, feeling, behavior, experiences, tasks, thoughts, reasoning, ideas, beliefs, values, attitudes, instruction, scaffolding, insight, etc.

In the model of Representational Theory of the Mind (RTM), knowledge is an evidence of truth including four properties: knowledge must be integrated by concepts; each concept can be identified by a name; names can be used to create propositions; and such propositions must be concluding [4]. Jerry Fodors' Language of Thought Hypothesis is one of RTM's extensions, stating that thoughts are represented by a language supported by principles of symbolic logic [5].

The Classic Theory of Concept Representation defines concepts as the representation of a mental object and a set of attributes, expressed through a specific mind language by symbols or patterns [6], but also considers descriptive capabilities, in the same way as in the Concepts as Theory Dependent Model [7].

Some psychological associative theories, such as connectionist, cognitive, and constructivist theories, try to understand and interpret mental processes. Connectionist theories state that knowledge can be described as a series of interconnected concepts, interconnected through associations, setting the basis of semantics as the means for knowledge representation [8]. Semantic knowledge and similarity representation have been proven to be drivers of reasoning for unstructured knowledge [9,10]. Traditional connectionist approaches do not account for causality, but they focus on the presence, number, or lack of associations. Constructivist theories do consider higher-order reasoning components, such as causality, probability, context, and adaptation, where each association group integrates different layers of thought differentiated by the strength of their associations, with concepts in the highest layer, and ideas in the lowest, leading to complex representations [8]. As of behavioral theories, they do not consider internal cognitive processes, but only external behaviors to different stimulus, and that is why behaviorist theories cannot explain thought in a desired depth [11].

Brown [12] states a knowledge model should be composed of theories, causal explanation, meaningful and arbitrary solutions; and states that theories are networks of concepts, causal explanations are facts, meaningful solutions are isolated pieces of knowledge, and arbitrary solutions are random decisions. And the Knowledge Space Theory model [13] defines knowledge as a group of questions combined with possible answers to form knowledge states, where their combinations create a congruent framework for knowledge.

Knowledge is sometimes defined as the psychological result of perception, learning and reasoning [9], meaning that knowledge can be generated, represented, stored and manipulated in order to obtain higher-level cognitive processes. To this regard, approaches such as the Unified Theory of Cognition [14] and the Adaptive Character of Thought [15], have influenced cognitive representation models, to the point that in the Cognitive Informatics Theoretical Framework [16], computerized knowledge representations are required to develop computerized systems with cognitive capabilities [17]. Metacognitive knowledge involves monitoring and reflecting on one's current thoughts, which includes both factual knowledge about the task, one's goals [18], as well as strategic knowledge, such as how and when consciously manage specific procedures to solve problems [19].

Common components in most of these models for knowledge and cognitive representation consider the following: Knowledge is composed of concepts, which have attributes and network structures [3]; concepts have associations with other concepts, and the associations have characteristics such as type, directionality, name, intension, extension, among others; and associations and concepts lead to dynamic structures, which tend to become stable in time, becoming factual knowledge. Concepts, associations and their structures apply for both factual (declarative) knowledge, and procedural knowledge, but concepts are more natural as factual knowledge. Concepts within procedural knowledge are integrated and referred as skills and competencies. Structured knowledge relies on information analysis using higher cognitive processes such as such as acquisition, ordering taxonomy, domain, direction of causality, and associations, among others. Unstructured knowledge relies on lower cognitive processes such as associative knowledge and similarity [9,20,21], and it may become structured when higher cognitive processes are applied through semantic and Bayesian causality networks, for example, although accomplishing only on an intuitive basis [9].

Main cognitive representation models include symbolic, non-symbolic, declarative, and distributed neural networks, differentiated only on how they represent reasoning [22].

1. Symbolic representation models include semantic networks, rule-based systems, frames, scripts and ontology-based concept maps.

1.1. Semantic networks are concept networks with nodes (concepts) and arcs (associations) [23], defined as a graphical equivalent for propositional logic [24]. Learning in semantic networks is represented by the association strength, or creating new concept associations. Semantic networks are mainly used to model declarative knowledge both in structured (associations are directed, including causality and hierarchy) and unstructured ways, but for procedural knowledge as well. Traditional semantic networks only used or lack associations, however MultiNet and Object Attribute Relation semantic networks provide more complex associations, integrating layers for knowledge composition [25].

1.2. Ruled-based systems focus on procedural knowledge and classification purposes in declarative knowledge [26]. They are sets of rules such as condition–action or if–then–else sentences. They are excellent in representing skills, learning and problem solving.

1.3. Frames are data-structures representing stereotyped situations to emulate human memory to store situations, combining procedural and declarative knowledge as an attempt to unify different approaches in psychology, linguistics and artificial intelligence [27]. Frames are similar to semantic networks, combining declarative and structured procedural knowledge, but unlike networks, frame symbols contain procedures and attributes for situation descriptions.

1.4. Alike frames, scripts are sentences describing an action, a plan to model networks similar to those of semantic networks. Script theory was originally designed to understand human language with episodic memory, and to explain higher aspects of cognition [28,29].

1.5. Ontology-based concept maps are abstract simplified views of the world, and explicit specifications of conceptualizations. They are flexible hierarchical logic structures that define relations between elements, and agreements in social contexts to accomplish objectives [30]. They are similar to taxonomies, semantic networks and symbolic systems [31] with formal conceptual descriptions for their associations.

2. Neural networks use symbols as unit of knowledge to represent concepts, and neuron-like activation patterns to identify concepts or ideas, or emulate cognitive processes of reconstruction of idea patterns even if concept parts are lost in the process, or to enhance patterns. Distributed models represent concepts as patterns, using associations between concepts, and association configurations as knowledge representation.

Reviewing more specific knowledge representation models, the Micro-theory model uses commonsense knowledge bases [32], combining multiple facts of subjective nature into a coherent knowledge base. However, they require a specialized language based on predicate logic semantics for information modelling and extraction.

MultiNet and Object Attribute Relation (OAR) are graphical-oriented models used for natural language processing, knowledge composition, and process specification, but they struggle to represent several contexts at a time [33]. MultiNet has context differentiators based on grammar attributes, but not for concept meaning in changing contexts. In OAR, the context is defined as a relation between objects and their attributes, it is more flexible, includes multiple non-concept contexts, and concepts are not dynamic [25].

The Memory Map (MM) model is a knowledge model that represents the interaction of concepts and skills in different contexts, including concepts with changing meaning according to contexts [3]. They are directed graphs showing context flexibility, open granularity, arbitrary level of concept atomicity, with dynamic hierarchies changing for each domain. The MM model is composed of concept units represented as round nodes, skill representation units represented as rectangular nodes, and associations represented as arcs. The concept, skill attributes, and their associations define the semantics and knowledge. Concept meaning changes depending on attributes tagged to domains. Concepts and skills have levels of knowledge with thresholds indicating structure and strength. Skill associations have an application-oriented nature and strength, belonging to at least one domain, where different contexts are formed from their combination. Attributes are combinations of concepts and associations. There is no distinction between objects and instantiations. The context or embodiment of semantic knowledge is composed of one or several domains.

Knowledge extraction is done by unguided recursive searches, returning relevant model segments to easily access information for open queries such as knowledge about certain concept/skill, concept attributes, relation of concepts in a particular domain, etc. New knowledge is acquired by associating it to existing knowledge.

The MM model has properties such as: Unlimited number of levels (granularity); concepts and skills can be integrated into hierarchies through roles and directionalities, and the combination of hierarchical domains generates new dynamic context-dependent hierarchies (taxonomies); compact network to avoid redundancy; unlimited number of units, hierarchy of attributes/associations, or knowledge depth; flexible structure, creating associations between units. The MM model has restrictions such as a domain may appear isolated, associations must be linked to units, and new concept/skill representation units must be created first, then their associations. A detailed MM Model example for an advanced learning environment can be consulted in [3]. The model adapts user profiles, containing user knowledge, interest, learning styles and emotional profiles. Other similar knowledge representation models can be consulted in [34,35]. Specific knowledge representation models applied to education are Intelligent Computer Aided Instruction ICAI, Intelligent Tutoring System ITS [36], and Adaptive Hypermedia [37].

## 3. The Mental Functional Representation Model

### 3.1. Model description, characteristics and modeling procedure

The functional modeling of cognitive processes, which shortly we will call Mental Functional Representation (MFR) model, is a symbolic and logical structural representation to describe complex cognitive concepts and processes from a wide domain of disciplines. MFR integrates the technical power of Adaptive Control Systems [38 p. 20], and more specifically to Model-reference Adaptive Control Systems, which have been successfully used in engineering to computationally control technical systems [38, p. 267]. An adaptive control system is a feedback control system capable of adjusting its characteristics in a changing environment so that some specified criteria are satisfied, and if the adaptive system is intelligent, then it can readapt and update its reference model, that is why they are suitable for emulating biological systems. At this stage of research, the current cognitive functional representation does not include propositional logic or quantitative aspects, since it is an adaptation to represent more complex unstructured theories as a more developed graphical mapping, but since intellectual adaptive control systems currently do that, it may be further developed in a more quantitative computational neuroscience approach. Alike the Memory Map model, MFR models include characteristics such as:

1. Directed associations with hierarchies, causality, and sequential logic.
2. Explicit input/output information, comparisons, feedback loops, and disturbance inputs affecting the cognitive process.
3. Functional blocks with attributes representing concepts, skills, experiences, contexts, processes, and open granularity subject to criteria and concept atomicity.
4. Capability to represent not only factual or declarative knowledge, but easily represent dynamic structures, strategic and procedural knowledge, and consequently, skills and competencies related to rule-based sets.
5. Representation of both factual and procedural knowledge of mainly structured knowledge of higher cognitive processes (acquisition, taxonomy, domain, direction causality, and association), but also unstructured knowledge of lower cognitive processes (such as associativity and similarity).
6. Graphical representation of association strength and potentiality to represent complex network structures and cognitive representation processes such as inductive, deductive, analogy and abduction reasoning.

But MFR includes additional characteristics: A special focus on feedback and learning loops or association cycles emulating the cognitive process of mental reconstruction of knowledge (constructivism); a comparison function; controllers that adapt the signals to correct the behavior of the system; and dramatization of external influencing factors.

The procedure to build MFR models is, in analogy to intellectual adaptive control systems but applied to a cognitive process, to start by sequentially representing the existing model, the inputs or references, the task or plant where the current process takes place, and is influenced by internal or external factors, the output of the task or plant, the feedback signals detecting the process status, the comparison of the current process with the existing model, a controlling measure, possible feedbacks to a more intelligent process of adaptation or update of the signals, that finalize in an update of the existing model, meaning that the model becomes more intelligent. This graphical representation is now applied in a series of examples of complex cognitive theories that, to our knowledge, have no current representation, and facilitate an easier understanding of complex theories in a logical and fast way, which is a useful tool in a number of disciplines

### 3.2. Mental Functional Representation Model of Jean Piaget's Theory of Intellectual Growth

Jean Piaget's Cognitive Constructivism Theory has two major parts: ages and stages predict what children can understand at different ages; and a theory of development, describing how learners develop cognitive abilities. Piaget's Theory of Intellectual Growth first emphasized the processes of conceptual change as interactions between existing cognitive structures and new experience [39]. Piaget's theory of cognitive development proposes man cannot immediately understand and use given information, but instead, humans construct own knowledge, schemas or mental models of the world through experience. Schemas are updated and enlarged through the processes of assimilation and accommodation [40].

Jean Piaget's Theory of Intellectual Growth, is considered a constructivism masterpiece and flagship of

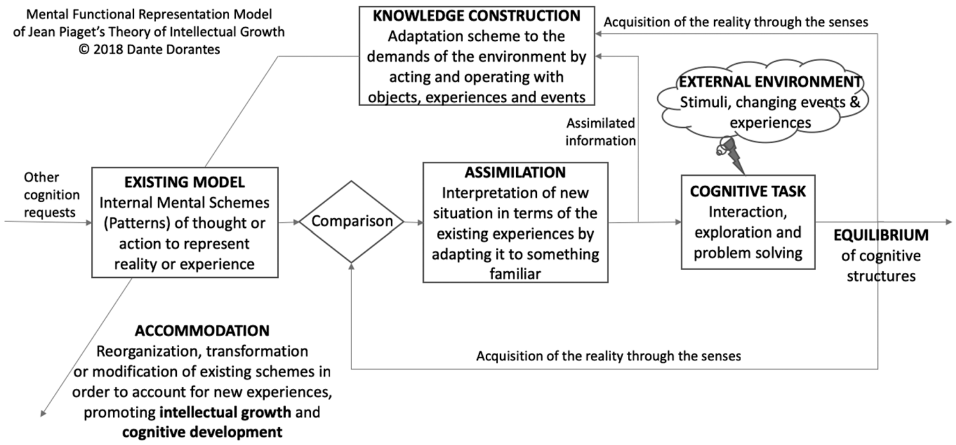


Fig. 1. Mental Functional Representation Model of Jean Piaget's Theory of Intellectual Growth

the cognitive sciences, education, and psychology. Hence, an interpretation of this model is developed and shown in fig. 1.

As it can be seen from fig. 1, an intellectual adaptive control system is suitable for representing Jean Piaget's theory. Besides meeting the traditional properties of semantic networks and advanced models such as the Memory Map Model, the MFR model introduces Piaget's own terminology and the following MFR characteristics:

1. «Feedback Loops» that acquire the perceptions from reality by sensing stimuli, events and experiences, but also after the preliminary Assimilation of the reality.
2. «Comparison Function» between the recent acquisition of the reality with the knowledge of the existing mental schemes.
3. «Learning Actions», such as the association arrow coming from «Knowledge Construction» to «Accommodation» by the modification of the existing schemes to account for the new experiences, and promoting intellectual growth. The «Learning Action» arrow is usually represented by diagonally crossing through the block that is to be enriched or modified. Learning actions are also common in neural networks and deep learning algorithms used in artificial intelligence. The application of MFR suggests that a «Learning Action» arrow is missing for the «Assimilation» block.
4. «Input signals», such as independent cognition requests, which, by the way, are not provided in Piaget's theory, but result as consequence of using such adaptive control system, where, for example, the signals may be seen as «inquiries», «goals», «orders», etc.
5. Regarding output signals, any outcome arrow leaving from a block unit can be considered as an output signal in control systems. In the model presented in the model, the output is the «Equilibrium of Cognitive Structures».

Besides, other elements are added to enrich the proposed model:

1. Influential Factor associations represented as «lightning» symbols are meant to affect a process by the direct or indirect action of other factors. A number of lightning symbols can be used to represent the level of influence or «strength» of the association in the process in a more visual fashion.
2. Clouds are meant to represent factors that may directly or indirectly affect a process, such as the «External Environment». The MFR model also helps to identify deficiencies in the represented model, since it may be suggested that an additional «cloud» may be missing above the «Existing Model» that may include «Beliefs», «Values» and «Memories», among others, that drive or may affect the existing model.

There are other MFR elements that are not included in the application example due to its specific nature, such as «Milestones» and «Hierarchies», but that may be used in other theories.

### 3.3. Mental Functional Representation Model of Antonio Damasio's Somatic Marker Hypothesis

A significant linkage between emotions and learning can be obtained by understanding the mechanism of Antonio Damasio's Somatic Marker Hypothesis [41]. To this regard, an MFR interpretation of this hypothesis including Damasio's own terminology has been developed in fig. 2, which explanation is given below.

Homeostasis is a life regulation mechanism that maintains the internal milieu physiological parameters (e. g. temperature, pH and nutrient levels) of a biological system within a range that facilitates survival and optimal function. It is composed of innate physiological «action programs» installed in the body's organs and brains aimed at maintaining or restoring homeostatic balance to cope with physiological needs, pain, well-being function, threats, and specific social interactions, but also for survival, flourishment, procreation, and, eventually, death. Action programs also may include changes in viscera and internal milieu (e. g. heart rate, breathing and hormonal secretion), striated muscle (facial expressions and running), and cognition (focusing attention and favoring ideas and modes of thinking) [42].

Main interoceptive pathways are the.

Action programs are deployed when either homeostasis changes are detected by the interoceptive system (nerve pathways and central nervous system nuclei such as the vagus nerve and the lamina I spinothalamocortical pathway), or external stimuli are detected by the

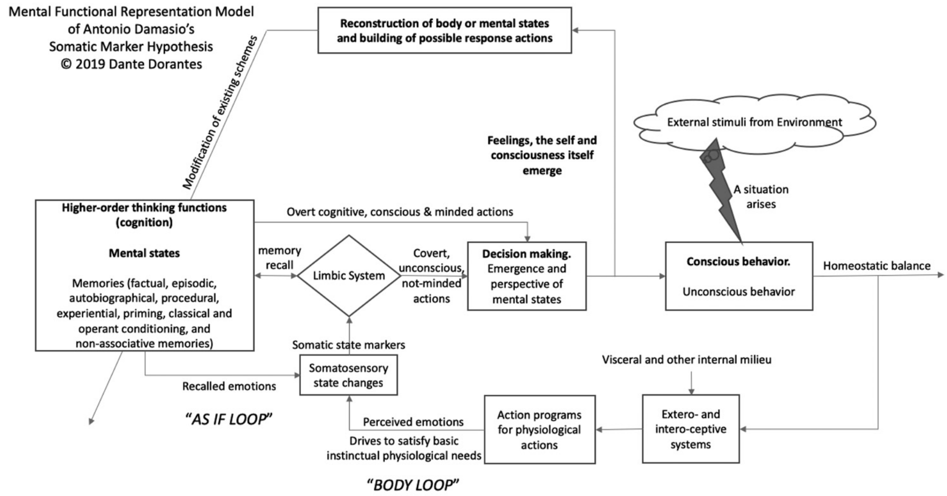


Fig. 2. Mental Functional Representation Model of Damasio's Somatic Marker Hypothesis

exteroceptive or proprioceptive senses such as the traditional: sight, hearing, touch, smell and taste, but also thermoception, magnetoception (direction), etc. These action programs generate «perceived emotions» and/or «drives» to satisfy basic instinctual physiological needs, such as hunger, thirst, libido, exploration and play, care of progeny and attachment to people. Perceived emotions and drives lead to somatosensory state changes by the so-called somatic state markers [41]. This pathway is called by Damasio the «body loop». But note that emotions can also appear from pure imagination («recalled emotions») without the intervention of physiological actions. This latter pathway is called the «as if loop». Emotions are action programs triggered by external stimuli (physically perceived or just recalled). Basic primal emotions include rage, fear, seeking, panic, lust, care and play [43].

The limbic system is composed of the amygdala, hippocampus, thalamus, hypothalamus, basal ganglia, and cingulate gyrus. The amygdala, the center of anxiety responsible for tagging emotional or motivational arousal along with the reward circuit, detects the state changes, makes a memory recall to the cortex through the hippocampus, responsible in the formation of new memories, so to interpret and map states changes.

After the interpretation of somatosensory body state changes, immediate «covert», unconscious not-minded actions lead to the emergence and perspective of mental states, that in turn make behave in a certain way. As that is happening, feelings, the self, and consciousness itself are elicited. Feelings are mental experiences of body states that arise as the brain interprets emotions, excluding meanings in the sense of thinking or intuition. Afterwards, a more accurate mental reconstruction of body or mental states takes place to build possible response actions, and modify of existing schemes, so that «overt» cognitive, conscious and minded actions for decision making are made to execute proper behaviors to cope with the current situation. Some other aspects within the block have bold texts, meaning that those parts are executed consciously as minded actions.

### 3.4. Mental Functional Representation of Dante Dorantes' Model of Soft Skills

Another MFR example is applied to depict Dante Dorantes' Model of Soft Skills (fig. 3), which also resembles the structure of an intelligent adaptive control system model. Indeed, with MFR modeling, it is possible to model general technical and non-technical processes that

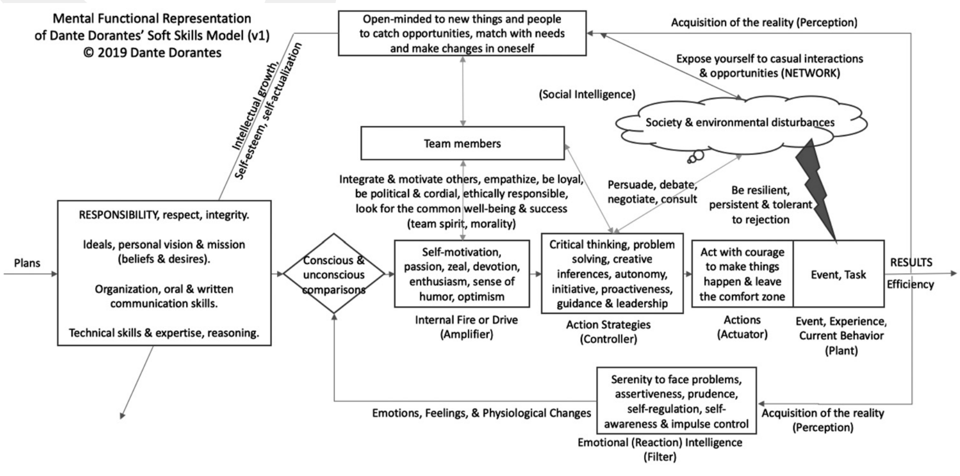


Fig. 3. Mental Functional Representation of Dante Dorantes' Soft Skills Model

include information acquisition, processing, comparison, actuation, interaction, and evolution to more complex models. The model in fig. 3 demonstrates how key aspects such as emotional intelligence, social intelligence (with colored arrows) and other nurtured skills that can be strengthened are integrated in the process. Note how a minimal set of professional knowledge, skills, values and attitudes are necessary to form a starting mental model. You can compare the advantages in accuracy, logic and neuroscience-based approach of the MFR model with one of the closest symbolic models in this specific field, the Wellman's Belief-Desire Reasoning Model [44, 45].

**Conclusion**

After a summary of the main types of representation models used for cognitive processes, a description of main specific examples of representation models and their properties, a functional graphical representation has been introduced and applied to the representation of a complex cognitive theories, such as Jean Piaget's Theory of Intellectual Growth, Antonio Damasio's Somatic Marker Hypothesis, and Dante Dorantes' Soft Skills Model.

The application of MFR to the concrete case of Piaget's theory unveils key properties such as: «Feedback Loops» acquiring perceptions from reality; «Comparison Function» between existing and actual schemes; «Learning Action» association arrows that modify existing schemes and that directly account for the new experiences and intellectual growth; «Input signals»; «Influential Factor» associations directly or indirectly affecting a process and introducing «strength» of the association; «Clouds» representing factors directly or indirectly affecting a process; «Milestones» and «Hierarchies». The application of the MFR model to Piaget's theory unveiled unexpected outcomes, demonstrating that MFR can be used to detect deficiencies or missing aspects of the original represented theories while they are mapped, such as a missing «cloud» above the «Existing Model» that might include «Beliefs», «Values» and «Memories», among others, that drive or affect the existing model; inputs to the theory; and lack of a «Learning Action» for the «Assimilation» block.

The MFR model presents, to our knowledge, the first graphical interpretation of this complex cognitive theory of Damasio's Somatic Marker Hypothesis. The development of this model significantly eases its description for teaching purposes for a wide audience.

At this stage, the MFR includes qualitative properties, and not propositional logic or quantitative association strengths, and activation patterns, that may be a topic of further development.

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