Integrating Emotional, Personal, and Social Intelligences in Complex Collective Decision-Making

Amine Chohra[1(✉)] and Chantal Natalie van der Wal[2]

[1] Images, Signals and Intelligent Systems Laboratory (LISSI EA/3956), Paris-East University (UPEC), Senart Institute of Technology, Lieusaint, 77127 Paris, France
chohra@u-pec.fr

[2] Department of Multi-Actor Systems, Faculty of Technology, Policy and Management, Delft University of Technology, Delft, The Netherlands
c.n.vanderwal@tudelft.nl

Abstract. This research tries to propose a general construct for computational models handling affect dedicated to complex and collective decision-making. The importance of integrating emotional, personal, and social intelligences, in complex individual and collective decision-making, is highlighted. Complex decision-making is approached from human to computational perspectives with the main perspective of complex problem solving. The objective of this paper is hence to: 1) examine how emotional, personal, and social intelligences capabilities contribute to effective collective decision-making in complex environments, 2) investigate how these capabilities can be computationally modeled to enable agents to build internal representations of the systems they manage, learn to process and respond to highly complex and dynamic information, and execute deliberate, prioritized cognitive and behavioral strategies to achieve desired outcomes in real-world problem solving, 3) identify current methodologies and approaches that integrate these forms of intelligence in agent-based systems, and 4) highlight promising future research directions and alternatives emerging from initial findings in this field. The main results are that this study identifies seven core mechanisms through which individual and group affect influence complex collective decision-making, integrating bottom-up and top-down emotional workflows into a single agent-based model. The implications of this study are that by combining affective, cognitive, and environmental parameters — weighted using statistical, knowledge-based, and machine learning methods — the model enables more adaptive, human-like behavior in artificial general intelligence systems.

Keywords: Complex collective decision-making · Artificial general intelligence · Emotional intelligence · Personal intelligences · Social intelligence · Affective learning · Social learning · Deep reinforcement learning · Cognitive modeling

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1 Introduction

At a purely theoretical level, complex decision-making that is strongly grounded in the European tradition can be defined from a complex problem solving perspective [1]. In this perspective, complex problem solving is defined as multi-stage decision-making [2], and as ubiquitous decision-making. Ubiquitous multi-stage decision-making necessitates to cope with problems – obstacles – (complex, multiple, dynamic, non-transparent, …) between an initial state and a desired final state exploiting behaviors, cognition, and multi-step, where only symptoms are available and reasons (unknown to the decision maker) have to be deduced [3]. Also, the behavior of decision, assigned from the experimental evolution of defined task parameters, has been explained by multi-stage decision-making theories, e.g., the decision maker stake as a winning probability consequence. This important aspect has deliberately ignored in complex problem solving theory. However, in order to develop individual distinctions, in problem solving and the behavior of decision, it is crucial to deal with the experimental evolution of task parameters. Thus, two research namely the complex problem solving could be complemented by multistage decision-making, and could lead to federate the behavior of decision and complex problem solving theories [2].

To make decisions, in complex and dynamic environment marred by imprecision and likelihood, is a core topics of decision theory, i.e., the decider has to take exactly one decision among two or more choices [2]. In classical decision-making research, such decisions have been mainly developed under non-dynamic or unique step decisions.

By another way, the decision maker has to take sets of decisions [4] under likelihood and imprecisions, particularly in multi-stage or dynamic decision task. In fact, in a series of several decisions, this kind of analysis rests on the hypothesis that these decisions are interdependent [2], i.e., decisions which are not a stand-alone decision as in unique step decision.

Consequently, in relating multi-stage decision to complex problem solving [2], the multi-stage decision task is explained as one in which the decision maker has to control a system.

Then, an open question is how to generalize the findings with easy tasks (easy, non-complex, without likelihood nor imprecision), ensuring their enforceability [2]. Therefore, in such tasks, it is very difficult to expect the behavior to generalize to very complex ones. However, the idea of the concept of sub-problem becomes crucial for a complex task in real-world or in theory and simulation, considering in such cases that a complex task holds one (or more) easy task as a sub-problem. Thus, from findings issued from advancements with multi-stage decision theories, behavior in such a sub-problem should be *predictable*. In fact, a complex problem could be subdivided in easier and autonomous sub-problems, making this hypothesis the back bone on which this consideration is based. In effect, this generalization notion that has proven to have such ability to predict for the behaviors of decision, could be promising in complex problem solving [2]. In a complex problem solving task, in order to build a mental model of the system to control [2], inner workings have to be more dynamic in data mining during the workflow to get information, and in using it.

In addition, in the complex problem solving field, main advances have been obtained with regard to themes and methodologies, particularly concerning two crucial points

[5], compared to the mid-1970s. First of all, in an effort to include the use of computer-simulated scenarios with which people have to interact and which should be controlled, the new paradigm for studying problem solving and decision-making under uncertainty require academic and public attentions. Afterward, in modern technologies, it is necessary to integrate the role of emotions [6] together with the role of human error [7].

Another crucial point, from an ecological perspective, the fact that professionals collaborate with others in missions of control and decision [8] which is pertinent was ignored for a long time. Fundamental research have hence to orient in the direction of control embedded in group workflows, as the cognitive workflows implied in interactions among persons in complex and dynamic environment marred by imprecision and likelihood. Consequently, contributing to the affective heterogeneity in the group [9] owing to the distinct traits, values and attitudes of members (individuals); the influence of affect in a group is more complex than the influence of affect in an individual.

Elsewhere, how humans and animals can generate behavioral patterns that are strongly synchronized with the environment to reach a desired goal? From this ability to generate adaptive behavior, two founding themes [10] arise: 1) the coordination of actions, and 2) the perception which should be included such that information about the world and the body allow to select appropriate actions and to adapt to world conditions. At a foundational level, the problem to govern the behavior of decision is hence intrinsically linked to the *perception* and *action.*

Main research questions are: 1) How can abilities of emotional, personal, and social intelligences be useful to complex collective decision-making in computational models? 2) How can such intelligent abilities be designed in order to allow complex collective decision-making: to design and construct a cognition representation of the system to control, to learn to handle information (complex and imprecise), and to perform a package of cognitions and actions (with planning and priorities), aiming to get closer to the desired final in solving real-world problems? 3) Which promising approaches/methodologies address answers to these questions? and 4) Based on findings in this domain, what could be the future directions (expected valuable)?

Research question 1) will be answered by discussing complex decision-making view, resulting in the cognitive complexity view, applied in an overview, of individual and group decision-making theories including affect in Sect. 2.

Research question 2) will be answered, following the cognitive complexity view, by highlighting useful abilities of emotional, personal, and social intelligences for complex collective decision-making, in Sect. 3, followed by affective, social, and deep reinforcement learning as well as cognitive modeling which are discussed in artificial general intelligence perspectives. Then, the affect integration in artificial general intelligence perspectives for complex collective decision-making is developed.

Research questions 3) and 4) will be answered in Sect. 4, where interesting approaches/methodologies and future directions for integrating such intelligence abilities in agent-based architectures for complex collective decision-making will be given. Finally, the main conclusions will be given in Sect. 5.

2 Complex Collective Decision-Making

In this Section, the complex decision-making view will be discussed first, which will then be applied in an overview of individual and collective decision-making theories including affect.

2.1 Complex Decision-Making

In real-world, humans depend on the professional expertise for complex decisions [11], e.g., in medical, doctors for consultations, sometimes placing their lives in their hands. Indeed, research on expertise started many years ago [12].

The definitions for expertise approved per several of European versus North American vary and lead to at best two complementary research areas affected by different events [1].

In addition, it is very important to consider the perspective that expertise is a prototype [11, 13, 14], inducing that humans have a shared idea of what an expert in a certain domain is. In fact, a prototype is mainly characterized by the following points:

1) different prototypes could belong to a certain domain,
2) prototypes are dynamic rather than static, and
3) several (no single) prototypes of the expert through groups taking decisions.

Consequently, expertise (involving cognition and ability to manage it with general and specific sub-processes) is a multi-aspect process of cognition (not entirely). It is crucial to handle also social conditions of its allocation. Thus, research on problem solving have to take into account the numerous aspects of prototypes of expertise to understand the work of an expert [11].

However, it is pertinent to notice, concerning problems requiring organization, that Europeans generally have not used large knowledge bases while Americans have, while concerning the cognitive complexity [11], it is most common in Europe than in America. In such European view, D. Dörner and A. J. Wearing points out the necessity to design and construct a cognition representation of the system to control. It is hence crucial to be able to hold it in working memory [11], in the goal to build up such a complex representation. Also, in order to learn a complex system, the capability to learn to cope with complex information (complex and imprecise) is crucial [11, 15], J. F. Beckmann and J. Guthke address the pertinence of learning.

In addition, including many aspects of complex problem solving definitions from different researchers [1] represents an interesting cognitive complexity perspective illustrated in Fig. 1, strongly grounded in the European tradition:

1) Occurs to cope with problems – obstacles – (complex, multiple, dynamic, non-transparent, …) between an initial state and a final desired state exploiting behaviors, cognition, and multistep.
2) Initial and final desired states, and problems between them are complex, change dynamically over solving time, and non-transparent.
3) Exact properties of the initial state, final desired state, and problems are initially unknown to the solver.

4) As only symptoms are available and causes have to be deduced [3], the underlying situation is non-transparent.
5) Implies the effective interaction between a solver and the environmental demands of the task, and involves a decision maker's cognitive, *emotional*, personal, and social capabilities.

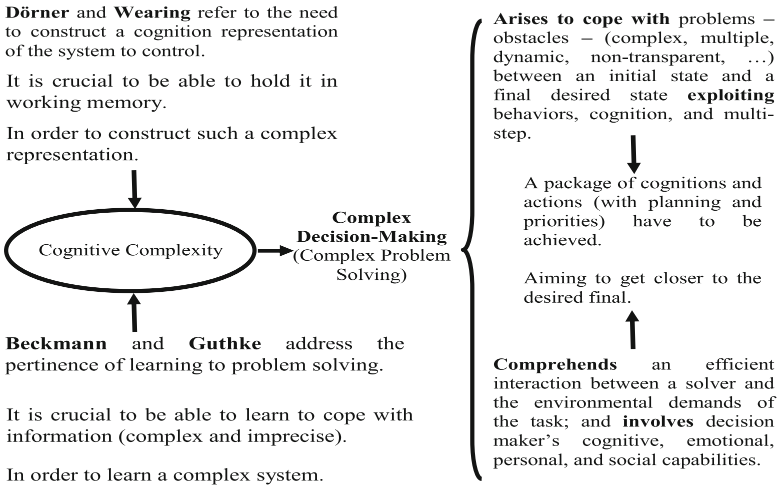

Fig. 1. The cognitive complexity perspective

2.2 Individual Decision-Making

Face to problems of complex real-world truths, a number of human thinking and planning deficiencies, i.e., shortcomings of objective drafting, predicting, decision-making, supervising, …, one can cites four (04) main reasons to such defects [16], which plays a key role in processing of trigger information (drives, emotions, personality, and memory systems) when dealing with very complex problems.

The Limited Ability of Conscious Thinking of Human. First, human is a kind of system efficient to monitor and control complex problems (highly routinized) [16]. Instinctively, it tries to use the limited resource of conscious thinking as economically as possible. This directly causes many error tendencies (formation of reductive hypothesis, linear extrapolation, and reluctance, …).

The Competence Feeling. Second, to have the feeling of being capable to efficiently act is extremely crucial [16].

The Weight of the Real Motive. Third, it is insufficient to handle the present and to solve the problems that arise at each time [16].

Forgetting. Fourth, humans are beings of the present and future, while the past exists for them only in shadowy contours [16].

Affect in Individual Decision-Making. Individual decision-making theory has been based classically on rational choice theory whereby one can rank options and choose the most satisfactory option based on computing [17]. Emotions play a small role in this kind of cost-benefits analyzes. Social and neuro-scientists began to consider again the role of emotion in decision-making which led to dual systems (or dual processes) models for the fast, automatic versus slow, deliberate decision-making processes, [18, 19]. Recently, the most widely discussed model of human decision-making in affective and social neuroscience is the somatic marker hypothesis whereby emotions can play a role in each decision via somatic markers in the brain [20, 21].

2.3 Collective Decision-Making

Deficiencies and Strengths in Collective Decision-Making. Group decision-making knows many advantages, such as that it can lead to more motivation and creativity, compared to individual decision-making [22, 23]. Other benefits can be that multiple people have more knowledge and expertise than an individual and that the combined knowledge could also lead to improved strategies and decisions [24, 25, 26]. Moreover, knowledge identification has been shown to be more successful in groups than individuals, in case the most influential person has the most knowledge [27]. Limitations are also known in group decision-making. For example, biased information pooling and confirmation bias are well known biases in group decision-making [28, 29]. Another limitation is group think – when consensus is prioritized over individual judgements of group members –, although it has also been criticized as an overgeneralized theory lacking evidence [30, 31].

Affect in Collective Decision-Making. The crucial point, from an ecological perspective, the fact that humans are usually cooperating with others in control and decision-making [8], which is pertinent, was ignored for a long time. Fundamental research should hence orient towards developing control implying group (collective) workflows. Consequently, contributing to the affective heterogeneity in the group [9, 32] owing to the distinct traits, values and attitudes of members (individuals); the influence of affect in a group is more complex than the influence of affect in an individual.

As the affective heterogeneity is an essential characteristic of the personality of an individual [9], the concept is embedded in the dispositional affectivity. Affect, influences hence the processes within a team and its resulting outcomes [32], i.e., being a deep level heterogeneity characteristic which is likely to influence team diversity.

The overtime interactions of teams and their comprising members embedded in a context shapes up the dynamic team environment [9]. These dynamic causal interactions can be local, global or contextual [9]. This induce the curiosity to examine the contextual role of group affective compositions [9].

For instance, studies have examined the convergence in-group affect [33] and its impact at individual and 5 persons team level [32]. Thus, owing to its divergent characteristic, affective diverse group can influence individual members' in a group [9]. Additionally, the group can have its own characteristic affective climate shaped by the collective affective tone and affective exchanges among members [9]. This further provides psychological safety to members and likely to influence their decision frame [9].

Extending this line of research, the dissertation further attempted to explore the contextual role of group affective diversity and group affective climate on the relationship between individual trait affect and individual performance [9].

Thus, the design and development of models with third-party data and models across disciplines [34] is hence required the expertise for specific issues.

3 Artificial General Intelligence for Complex Collective Decision-Making

In this section, the importance of integrating emotional, personal, and social intelligences, in complex individual and collective decision-making, is highlighted. Then, the role of affective, social, and deep reinforcement learnings as well as cognitive modeling is developed. Afterwards, the affect integration in artificial general intelligence perspectives for complex collective decision-making is developed.

3.1 Emotional, Personal, Social Intelligences

Intelligences described in [35] are divided into cool and hot groups where verbal-understanding and perceptual organizational intelligences constitute the cool group of intelligences; focusing on general and not-personal information (verbal meanings or visual patterns). While personal information, and social constitute hot intelligences; relevant and hence more emotionally-charged in nature (feelings and relationships).

However, these cool and hot intelligences might be integrated into a coherent theoretical structure [36]; i.e., hot: abilities involving emotionally-salient information, the processing of highly charged and personally significant information such as emotions, personality, and social relations, and cool: abilities involving perceptual processing and logical reasoning.

Emotional Intelligence. Several researchers have developed emotional intelligence [32, 39, 40, 41, 42] where emotional intelligence refers to the ability to perceive, control, and evaluate emotions.

In the influential work [37] emotional intelligence is defined as feelings and emotions: the subset of social intelligence that involves the ability to monitor one's own and others, and to discriminate among them and to use this information to guide one's thinking and actions. Whereas emotional intelligence is defined in [38] as: perception, appraisal, and expression of emotion, emotional facilitation of thinking, understanding and analyzing emotions, regulation of emotion in oneself and others to promote emotional and intellectual growth.

Personal Intelligences. Two forms of personal intelligence have been defined in [43], one directed toward oneself and one directed toward other persons:

Personal Intelligence Form Directed Toward Oneself. In its most primitive form, the intrapersonal intelligence represents little more than the capacity to distinguish a feeling of pleasure from one of pain. To become more involved in or to withdraw from a situation, i.e., hence on the basis of such discrimination. At its most advanced level, to detect and to symbolize, complex and highly differentiated sets of feelings, are allowed by intrapersonal knowledge.

Personal Intelligence Form Directed Toward Other Persons. This form turns outward to other individuals. How to do differentiations (among other individuals) is the core capacity (among their moods, temperaments, drives, and intentions). This essentially leads to group influence notion, e.g., by influencing a group of heterogenous individuals to behave along desired goals.

In addition, an interesting definition of personal intelligence is given in [35].

Social Intelligence. The rudiments of social intelligence as developed in [44] rely on four separate abilities that have been identified in [43] namely organizing groups (leaders), negotiating solutions (mediators), personal connection (empathy), and social analysis.

3.2 Affective, Social, and Deep Reinforcement Learnings – Cognitive Modeling

Affective, Social, and Deep Reinforcement Learnings. Scientific findings, in 1990s, established first basics to comprehend the role of affect in learning [45, 46].

Affective Learning. It has been attested in [45], that when basic mechanisms of emotion are missing in the brain, then intelligent functioning is slowed down [45]. Afterwards, several improvements have been achieved on the most fundamental level [45], in multiple disciplines (neuroscience, psychology, and cognitive science) supporting a perspective of affect, long time ignored or marginalized, as complexly intertwined with cognition (thinking, and performing important functions) in guiding rational behavior, memory retrieval, decision-making, and creativity.

Social Learning. It has been addressed (through Hullian learning theory) in [47], while J. Dollard and N. Miller addressed social learning theory. More, A. Bandura provided a pertinent comprehensive theory of personality (recognizing the external workflows of reinforcement and punishment and the internal cognitive workflows that make humans so complex).

Deep Reinforcement Learning. Multiple conflicting objectives, which must be balanced based on their relative importance, are inherent to many real-world decision problems. In the dynamic weights setting, the relative importance changes over time leading to specialized algorithms, e.g., dynamic weights in multi-objective deep reinforcement learning developed in [48].

Agents have to construct, to cope with real-world complexity, efficient representations of the environment from high-dimensional sensory inputs, and use these to generalize past experience to new situations. Especially the sub-field of deep reinforcement learning, where neural networks are used for approximation of functions, has recently yielded some impressive results [49].

Cognitive Modeling. Computational models will play an important role [50, 51], at higher-order cognition.

3.3 Affect Integration in Artificial General Intelligence Perspectives for Complex Collective Decision-Making

Artificial general intelligence research, considered as a subset of Artificial Intelligence research, has also combined theory and experimentation in various and complex ways [52]. Its refers to [53]:

1) Artificial Intelligence research in which "intelligence" is treated as a general-purpose ability.
2) Implying the capability to largely generalize to further domains [54].

Elsewhere, emotion and motivation play a crucial role in directing and structuring intelligent perception and action [55]. More, any functional model that strives to explain the full breadth of mental function will have to tackle the question of understanding emotion, affective states, and motivational dynamics [55].

Thus, for complex collective decision-making, the affect integration consists:

1) to establish the relationship between motives, affects, and higher-level emotions,
2) to give directions for their integration in computational models, with a focus on enabling autonomous goal-setting and learning [55].

Diverse workflows through which group affect arise have been addressed, at upper appraisal levels, from organizational science, sociology, and psychology [56]. These workflows for arising group affect have been defined as: inclination, interaction, institutionalization, and identification. Further, in [32, 57], group affect has been defined in two core ways namely a top-down and a bottom-up.

Furthermore, current approaches stressing the notion of cognition as perception-action cycle controlled by internal schemata, priors, and decisions [14] may be is one challenge to cope with the theory where the notion of knowledge as being an active process that is build up by the learner and the one relying on the stimulus [58]. In fact, in order to perform tasks successfully, across different problem domains (general human capability implying its different forms of intelligence), deep machine learning and reinforcement learning should be combined [59].

The generalization ability of mammals effectively matches drivers perceived in their environment with patterns previously (in time) remarked. While the decision under imprecision and likelihood, is linked with the generalization which offers large issue deduction, is another critical human skill. Following this, at a global level, intelligence involves two complementary sub-workflows: *perception* and *actuation* [59].

4 Approaches/Methodologies and Future Directions

In this Section, interesting approaches/methodologies and future directions for applying the group affect integration in agent-based architectures are discussed.

4.1 General Construct

In this Section, seven diverse workflows, crucial for collective affect decision-making, ranging from individual to group and emerging workflows are differentiated, from which a general construct is proposed. The main workflows of group affect from three different domain views namely psychological, social neuroscience, and computer science have been investigated to generate a general construct [60], illustrated in Fig. 2.

Individual Workflows: individual-related level experiences they imply emotions, moods, feelings, and emotional intelligence

Group Workflows: collective-related level effects they imply emotional influence, homogeneousness, circular action, and suggestibility

Bottom-Up Workflows: from the 'sum of its parts': a) Implicit and Explicit Workflows from Collective Interactions, b) Arising Collective Behaviors under Diverse Collective Situations, and c) Affective Compositional Collective Consequencess [57], [38]

Top-Down Workflows: viewed as 'a whole': a) Collective's Affective Construct, b) Affective Construct Group Consequences on Social Interactions, c) Expand-and-Construct Principe, and d) Positive and Negative Consequences [57], [38]

Bottom-Up and Top-Down Workflows: Combination of Workflows

Influence Workflows: How Does Collective Emotion Influence the Collective Performance?

Feed Back Workflows: How Does Collective Emotion Feed Back into the Collective's Affective System?

Fig. 2. A general construct from main workflows

4.2 Perception-Action Cycle

In this Section, a perception-action cycle is proposed, for the decision-making modeling (agent) handling affect, as an approach highlighting the cognition process as perception-action cycle governed by internal patterns, pre-conditions, and decisions, as discussed in Sect. 3.3.

Motivated by works in [10, 59] the appraisal levels of the perception-action cycle are proposed in Fig. 3 [61] for the agent-environment interactions.

The agent and environment are double-bonded (perception and action levels):

1) Perception appraisal level: an information operating mapping properties of the agent-environment system into informational variables, under the theories of ecological perception-action approach to the control of behavior.
2) Action appraisal level: an actuation operating changing the vector of action variables into muscle activation patterns that produce forces in the environment, action is hence characterized as a relation defined over the agent, causal forces, and the environment.

Thus, the evolutionary and objective-directed characters (surpassing sometimes the desired objectives) of the behavior (which adapts) arises from these local interactions between an agent controlled by the control theories and an environment controlled by the physics theories.

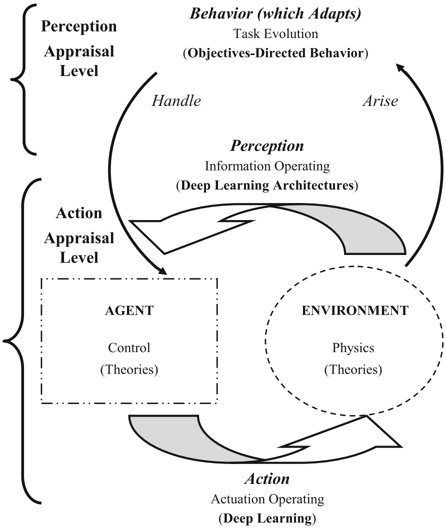

Fig. 3. Agent-environment interactions (perception-action cycle)

4.3 Cognitive Reasoning Systems in Cognitive Science

In this Section, the cognitive reasoning systems in cognitive science such as cognitive modeling, commonsense reasoning, and sub-symbolic approaches, are discussed.

Different progresses in cognitive science [62] of cognitive computing in favor of computational modeling have led to cognitive reasoning [63] which is becoming essential for the integration of affect in decision-making of computational models which deal with complexity, dynamics, and fuzziness of real-life problems.

Indeed, cognitive reasoning systems include cognitive modeling, commonsense reasoning, and sub-symbolic approaches which could be defined as:

1) *Modeling the cognition ('mental'):* is a trans-disciplinary domain exploiting approaches such as computer science, Artificial Intelligence and cognitive psychology to build computational models for the workflows of the human cognition [63];
2) *Reasoning with a common-sense:* it can be globally comprehended as daily reasoning of humans achieving life activities [64, 65];
3) *Sub-symbolic approaches:* a paradigm with low explainability but high accuracy performance.

Also, to handle the reasoning with common-sense on task evolution, the reasoning on cognition is frequently coupled with deep learning [63], e.g., case of issues in natural wording (instead of logical programs or equivalents).

4.4 Weighted Influence of Parameters at Different Stages and Levels (E.g., Individual, Social, and Environmental)

In this Section, one of the main problems is investigated: on how to weight the influence of parameters at different stages and levels (e.g., individual, social, environmental), encountered when designing and handling affect in complex collective decision-making.

Generally, the methodology relies on the psychology of thinking, where the complex problem solving is developed under computers-based scripts. This induces the human individuals (which could be organized in groups) for data mining and governing complex dynamic (behavior) systems [66]. In fact, to do that, such individuals have to previously acquire the necessary cognition. To elaborate this and apply it, subjects (agent and/or humans) are confronted with computer-simulated scenarios [66]. A differentiation is hence necessary: between factors influencing complex problem solving resulting from the individual, as well as from the situational, and from the system attributes [66] in such computer-simulated scenarios. In fact, performance measures, and consequently on the quality of the results are influenced by this separation of person factors, situational determinants of complex problem solving, and system characteristics.

Several parameters have to be chosen by modeler that has an influence on individual and collective behaviors. Theses parameters can be linked and classified in different ways. For instance, take a crowd evacuation problem that needs to be translated to an agent-based simulation [67–70]. Many factors will influence the evacuation behaviors and evacuation time, such as:

1) environmental factors (e.g., doors, signs, …),
2) cognitive factors, (learning and adaptation agent capabilities, e.g., interpretation of signs, …),
3) emotional factors (e.g., six basic emotions: anger, disgust, fear, joy, sadness, surprise, or the somatic marker hypothesis – somatic feedback, "+" reward, "-" punishment, or moods and feelings),
4) social and cultural factors (e.g., social influence, imitation, culture, relations to other people),
5) physical factors (e.g., body size, height, physical disabilities),
6) individual factors (e.g., the two interpretations of a personality taxonomy [71], through the models of personality structure namely: the model based on five factors [72], and the six-factor (HEXACO) model involving Honesty–Humility (H), Emotionality (E), eXtraversion (X), Agreeableness (A), Conscientiousness (C), and Openness to Experience (O) [73–76]).

After a classification of influent parameters, the problem is then what could be the influence degree of each class on the individual and collective behaviors in a general problem? Such a problem – which is not easy – could be solved with different manners depending on how such influence classes could be combined involving classes of varying influence importance to the decision-making and the relative influence importance of the classes is required. This could be obtained by assigning a weight to each influence class in a linear combination. Note that in this case the influences are issued from different class nature and several linear as well as non-linear combinations are possible.

Then, such weights could be obtained using:

1) Statistical methods: statistically compare and analyze different results, expecting that these methods even if they will not give us the appropriate (exact value of each weight) degrees of influences, they will have the merit at least to demonstrate that the influences should be differently weighted in their degrees (and not of the same degrees).
2) Knowledge-based methods (probabilistic, fuzzy logic, and neutrosophic logic theories): these methods are globally based on expert's knowledge [77–79]. These methods are the hardest methods, since they require to analyze many references in the literature in different fields: cognitive science, social, psychological, and emotional. Then, to deduce some interesting and important orientations (from skills, experiences, …) which will serve us to approximately define different influence degrees. This is, in fact, another challenge.
3) Machine learning methods: these methods consist of acquiring the influence degrees, e.g., using artificial neural networks [61], or e.g., using the reinforcement learning [80–82] of agents, from the environment interaction, particularly using modular reinforcement learning [83]. The challenge of these methods is directly related to the main problem of reinforcement learning with regard to the number of states which is too big, in general in real-life applications (or in near-real applications in simulation). Fortunately, this problem has many solutions from the deep reinforcement learning (e.g., modular neural networks).

5 Conclusion

The goal of this paper was to explore how affective, personal, and social intelligences can enhance complex collective decision-making processes.

Seven different core mechanisms, in group affect decision-making, were distinguished ranging from individual to group and emerging processes, from which a general construct is suggested. Then, a perception-action cycle was proposed for decision-making modeling (agent) handling affect. Such approach highlights the cognition process as perception-action cycle governed by internal patterns, pre-conditions, and decisions.

In addition, the main problems encountered when designing and integrating group affect, in computational models of complex decision-making, were discussed. Solutions addressed cognitive reasoning systems (cognitive modeling, commonsense reasoning, and sub-symbolic approaches) in cognitive science; and ideas on how to weight the influence of parameters at different stages and levels (e.g., individual, social, environmental).

It should be interesting to investigate, in future, a computational architecture for agent-based group decision-making modeling handling the abilities of emotional, personal, and social intelligences in the perspective of applying it to real-world problems [84].

Theoretical implications of this work are: 1) the inclusion of affect in computational models challenges traditional computational paradigms that focus primarily on logic and reasoning, and 2) the integration of concepts from psychology, sociology, neuroscience, and computer science into a single computational general intelligence construct highlights a need for interdisciplinary theory development. The practical implication of this work is that the proposed mechanisms for group affect (e.g., emotional influence, group performance feedback, bottom-up and top-down emergence) can be directly implemented into multi-agent systems for simulations in social robotics, emergency response, or virtual environments. Including affective parameters (emotional, motivational, and social) improves decision-making in complex and uncertain environments by enabling systems to better emulate human-like adaptive behavior and context sensitivity**.**

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