Future AI in crisis management: Proposing a bio-inspired, neuro-symbolic architecture

Aurélie Montarnal
IMT Mines Albi
aurelie.montarnal@mines-albi.fr

Frédérick Bénaben
IMT Mines Albi
frederick.benaben@mines-albi.fr

Rob Grace
Texas Tech University
rob.grace@ttu.edu

Grégoire Borst
LaPsyDÉ - UMR CNRS 8240, Université Paris Cité
gregoire.borst@parisdescartes.fr

Paul Gaborit
IMT Mines Albi
paul.gaborit@mines-albi.fr

ABSTRACT

This paper addresses the evolving relationship between Artificial Intelligence (AI) and crisis management, spanning over a decade. Initially sparked by social sciences' interest and facilitated by abundant data, particularly from social media, the collaboration between these fields has streamlined decision-making processes. However, the distinctive, uncertain nature of crises presents challenges in adapting AI to varying contexts. In exploring existing frameworks like Common Operational Picture (COP), Situational Awareness (SA), and Sensemaking, the paper finds a potential misalignment between recent AI architectures, predominantly symbolic or neural, and these established frameworks. To bridge this gap, the paper proposes a bio-inspired neuro-symbolic AI architecture, emphasizing its application at the Sensemaking level during crisis data exploitation. Leveraging insights from neurosciences advancements, the paper aims to enhance the adaptability and effectiveness of AI systems in crisis situations.

Keywords

Situation Awareness, Sensemaking, neuro-symbolic AI, neurosciences

INTRODUCTION

For more than a decade, the crisis management community has been interested in using Artificial Intelligence (AI) to support decision-makers and their information needs (Palen et al., 2020). This enthusiasm first came from the social sciences, whose studies were historically prevalent in the study of past crisis management, and naturally joined the field of AI thanks to easier access to voluminous streams of data - notably social media - that can be exploited computationally(Palen & Anderson, 2016). The literature shows that the two fields have been able to work together quickly and effectively, and the richness of the inter-disciplinary collaborations set in motion on this occasion no longer needs to be demonstrated, particularly within the ISCRAM community (Reuter et al., 2018).

With this in mind, the last few years have seen a strong interest in the application of AI to quite specific and not always generalizable tasks. While the basic issue remains that of saving crisis managers time and resources in accessing and exploiting rich, heterogeneous data flows, the challenges are not limited to this. The context of a crisis is unique in that it is by definition uncertain, sometimes unknown, and each time different in the course of events.

Slam et al. (2015) summarizes three challenges for designing a decision-support system for crisis management: represent knowledge, reason about knowledge in real-time, and adapt knowledge to unknown situations. Knowledge representation capability refers directly to the decision support system's ability to process data flows in real time in order to establish an up-to-date map of the crisis context and its events. The systems affected by crises are generally complex, and the decision-making process, in its first stage of understanding the situation, is just as complex, involving a wide range of expertise and points of view. AI, with its ability to deal with large data flows and apply logical rules, is a strong ally to promptly address this first information need problem in decision support systems. In the literature, this ability of a decision support system to process data (human or machine) in order to understand a crisis situation is generally grouped under three terms, each with specific levels of processing and complexity: *Common Operational Picture (COP)*, *Situational Awareness (SA)* and *Sensemaking*. Although the definitions were clearly formulated a few years ago, the work proposed in AI, influenced since then by a remarkable progress in technology, has sometimes been developed independently.

While most AI architectures developed for crisis management are based almost exclusively on symbolic or neural architecture, neuro-symbolic architectures seem more likely to solve certain challenges, especially at the Sensemaking level. Yet, neuro-symbolic AI architectures, beside several attempt, still do not meet the level of expectation of a Sensemaking-level AI support. In parallel, neurosciences have undergo a strong progress in the last years and human brain cognition processes are now better known, providing promising inspiration for future AIs.

In this context, this paper serves two purposes. The second Section of this paper questions the current alignment between state-of-the-art AI architecture and the information needs of crisis responders formulated in COP, SA, and Sensemaking literatures. Hence, it focuses on a litterature review of the three formulations of informational needs and discusses the underlying processes for information extraction by individual or (inter-)organizational crisis responders. The third Section proposes a bio-inspired neuro-symbolic AI architecture to address the Sensemaking-level challenges in the exploitaiton of data to extract crisis comprehensive situation models. Finally, the conclusion will provide an opportunity to take a closer look at the current limits of the approach and future work.

LITERATURE REVIEW

Informational Needs and Human Processing

Common Operational Picture

The aim of a COP, which is generally the heart of Command and Control Systems, is to provide decision-makers with a *single* perceived and shared situational picture (Kuusisto et al., 2005). In essence, the SA-based decision-making paradigm involves the actor utilizing their knowledge to make decisions based on their perception, understanding, and projection of the dynamic environment they are operating in. On the other hand, COP serves as an information-sharing tool, allowing for the unambiguous modeling of a situation and therefore facilitating a fluid communication between actors.

Situational Awareness

SA is generally associated with Endsley (1995)'s famous framework, which involves perceiving, understanding, and projecting a situation as a reliable basis for decision-making. First, Endsley unambiguously positions SA as a state of knowledge, and refers to the process of accessing this state as *situation assessment*, enabling to "achieve, acquire and maintain SA". Second, in SA, Endlsey includes knowledge of the state of a dynamic environment and explicitly excludes any static knowledge or expertise. While the boundaries of this dynamic state of knowledge of a system in motion are clear, they gain in complexity in "real life", where decisions reflect coordination and even collaboration between several actors, just as in crisis management. Here again, Endsley's framework proposes a definition of *team SA*, i.e. a complete SA of each individual concerning his or her responsibilities, with areas of overlap between actors being acquired individually or through information sharing.

According to this definition of a state of knowledge necessary for decision-making, the acquisition process itself underpins cognitive mechanisms specific to human reasoning. This definition aligns with the broader understanding of reasoning by Leighton and Sternberg (2004) : "reasoning is broadly defined as the process of drawing conclusions. [...] these conclusions inform problem-solving and decision-making endeavors", thus also unifying goal-oriented paradigms, which in turn require the implementation of an attention mechanism on the part of the actor. Although Flach (2015)'s argument is probably beyond the scope of this paper, he stresses the importance of thinking about SA within a contextualized framework in which "meaning is defined in terms of functional significance or utility", and questions the status or rather the influence of sociotechnical systems ("thinking machines") in this framework.

SA can be realized through the individual access to *actionable information*. Actionable information is defined by Zade et al. (2018) as " the right information [that] reach the right person at the right time". Coche et al. (2021) operationalize the actionable information under four criteria: relevant, timely, precise and reliable. Therefore, the automation of actionable information mining comes as a crucial challenge to support SA with intelligent systems.

Sensemaking

Finally, the process of Sensemaking, although variously defined in the literature (Klein et al., 2007; Pirolli & Card, 2005), refers to processes "by which people seek plausibly to understand ambiguous, equivocal or confusing issues or events" (Brown et al., 2015). The term "Sensemaking" originates from Organizational Studies, but there is no consensus in the literature regarding its mechanism (Brown et al., 2015; Muhren & Van de Walle, 2010; Weick et al., 2005). The notion of the collective is called into question, as Sensemaking may be understood as an individual and/or collective process. In the context of crisis management, Weick's work in favor of a collective Sensemaking process is best summed up in the 7 properties summed up in the following citation: "Taken together these properties suggest that increased skill at Sensemaking should occur when people are *socialized* to make do, be resilient, treat constraints as *self-imposed*, strive for *plausibility*, *keep showing up*, use *retrospect* to get a sense of direction, and *articulate descriptions* that energize. These are micro-level actions. They are *small actions*. But they are small actions with large consequences." (Weick et al., 2005).

On COP, SA and Sensemaking Integration

As a conclusion of this section, we demonstrate that comprehending a situation, a crucial step towards decision-making in a dynamic environment, must be considered at three interconnected levels: (i) the cognitive processes that underpin human reasoning; (ii) the social context that influences individual evolutions as much as individuals influence social behavior; and (iii) the importance of a common language with a moderate level of interpretation, so as to favor non-ambiguous shared modeling.

Moreover, an AI to support Sensemaking, in its collective process definition, should address a two-dimensional challenge:

- *horizontal dimension* - the expertise and type of data to be processed fluctuate according to the type of crisis and the specific context;
- *vertical dimension* - the granularity of the information extracted from the data varies directly with the level of crisis (e.g. regional or national) and the decision-making level of the decision-maker who has the AI tools in hand (Benaben et al., 2016).

Artificial Intelligence to Meet Informational Needs

The field of crisis management, like many other fields in recent years, is showing strong growth in the use of AI, as can be seen from Figure 1, representing the number of publications on Scopus in response to the search "('crisis management' or 'emergency management') AND 'artificial intelligence'".

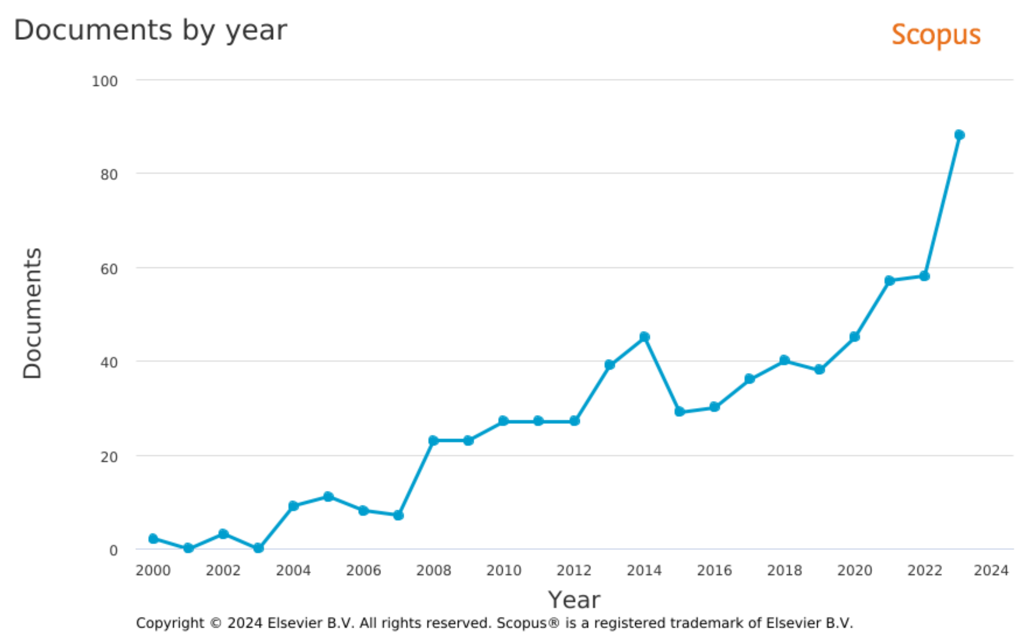

Figure 1. Evolution of the number of published paper on the Scopus scientific database, search string *TITLE-ABS-KEY ("artificial intelligence" AND ("crisis management" OR "emergency management"))*.

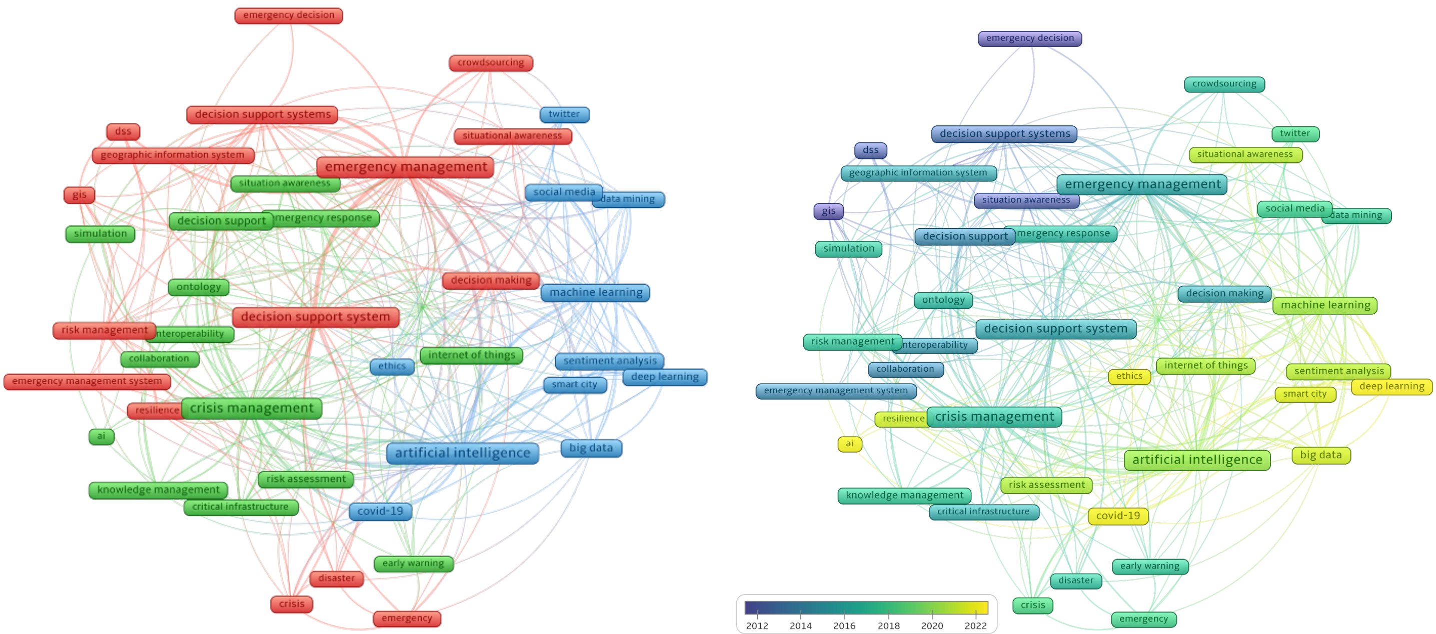

Figure 2. Usage of the authors keywords by clusters - on the right - of interest and year - on the left , search string on Scopus database *TITLE-ABS-KEY (("artificial intelligence" OR "AI") AND (emergency OR crisis) AND management AND survey)*. Generated with VOSviewer visualization software.

A keyword study (see Figure 2) highlights the use of AI for:

- **Achievements and purposes - red cluster** : Includes operational research and decision support systems to optimize decisions.
- **Knowledge-based systems - green cluster** : Includes systems for situational awareness or early warning systems based on expertise modeling.
- **Machine learning-based systems - blue cluster** : Includes big data (and especially social media data) processing with machine and deep learning methods.

The first cluster is excluded from this study, as it focuses on optimized decision-making rather than information processing itself.

In the following two sections, we provide an overview of the current state of the art in: (i) knowledge-based systems that enable static modeling of expertise on the basis of pre-defined concepts; (ii) systems based on learning approaches to solve specific problems in data processing; and (iii) systems that attempt to approach a multi-dimensional interpretation of data.

In order to target article searches in the Scopus database, the search strings were refined using keywords from the green (i) and blue (ii) clusters.

Knowledge-Based and Expert Systems : Symbolic Approaches

Knowledge-based and expert systems are based on a triptych consisting of a schema or structure for representing knowledge, a knowledge base subject to the representation schema, which embeds and computerizes the knowledge accumulated by domain experts, and a set of inference rules providing the system with logical reasoning for discovering or updating knowledge.

Numerous studies have focused on the implementation of such systems to support the information processing efforts of crisis decision-makers. Regarding knowledge representation, the terms meta-model (derived from model-driven engineering - MDE) and ontology are used as references: whatever the formalism used, it is a question of one way or another for experts to conceptualize the semantics of a domain, most often by qualifying the classes of interest and the relationships that link them. Works such as (Alheadary, 2023; Christensen & Madsen, 2020; Correia et al., 2018; Kontopoulos et al., 2018) offer structured and possibly populated knowledge bases relating to the crisis management domain.

A reasoning layer, based on inference, can then be added on top of the knowledge base to take advantage of it, through the use of expert rules. Benaben et al. (2020), Rezaei and Vahidnia (2023), and Slam et al. (2015) propose this type of inference mechanism in their work, enabling them to offer users of the software developed an explicable framework of recommendations.

In order to make knowledge-based systems more reactive and autonomous, they have also been augmented by paradigms such as Complex Event Processing (CEP), enabling data to be received (from sensors, for example) and processed by rules in real time in order to relate it to knowledge already stored in the system, possibly triggering inferences. Systems of this kind, as proposed by Barthe-Delanoë et al. (2014), Fertier et al. (2020), and Mijović et al. (2019), have been widely used in the development of early warning systems.

In view of the uses to which they have been put, knowledge-based systems have undeniable advantages. In particular, they enable:

- Establish and unambiguously represent a semantic framework, thus ensuring unified interoperability;
- To a certain extent, to reason (by logical rules possibly integrating the notion of uncertainty) about knowledge with speed and explicability in order to draw conclusions.

Nevertheless, their lack of genericity and adaptability, due to a semantics fixed in a predefined semantic framework, makes it difficult for these systems to take advantage of heterogeneous data flows.

All these features qualify knowledge-based systems as ideal candidates for the realization of a COP.

Single-Task Performance Systems : Machine and Deep Learning Approaches

The use of AI learning techniques has been growing steadily over the past fifteen years. This growth can be relatively easily explained by the era of Big Data, with its increasing capacity to collect data (from connected and distributed sensors, imaging systems and social media, in particular) and store it at low cost, to drive machine learning and deep learning algorithms.

While the Scopus search ”(’crisis management’ OR ’emergency management’) AND (’machine learning’ OR ’deep learning’ OR ’big data’ OR ’data mining’)” has returned 792 papers from conferences and scientific journals since 2015 (as of February 13, 2024), adding the criteria ”(’social media’ OR ’social network*’ OR ’twitter’ OR ’tweet*’)” brings up 234 papers. In 2015, Imran et al. (2015) publish a survey on the use of AI methods to process social media messages for mass emergencies. Imran et al. explore three main challenges: data pre-processing, event detection and characterization, and aggregation into actionable information for end-users. Whatever the challenge addressed, the AI methods listed in this article remain classic, i.e. trained to perform the specific, often supervised tasks of topic modeling, message classification, named entity recognition and text summarization.

The observation can also be generalized to AI applications in crisis management for processing all other types of data (satellite and aerial imagery, sensors, remote sensing robotics, for instance), as shown by the very comprehensive systematic literature recently proposed by Sun et al. (2020) with the development of AIs highly specific to the tasks they perform. Kyrkou et al. (2023) raises the challenges that the state of the art is currently tackling:

- a broadening of the data types processed, using multi-modal models to solve problems of heterogeneity (joint processing of text and images, in particular)
- the ability to generalize and adapt AIs to new situations by generating learning data (through generative AI or the use of digital twins, lowering in the same way the cost and time of training datasets devlopment to supervise AIs)
- the enhancement of user confidence through explicability
- algorithm security

Today’s learning-based AI methods are reviving the literature on automated data processing in crisis management with definite avatars:

- far greater generalization capacity than knowledge-based systems, making them highly adaptable
- deeper and deeper learning thanks to the use and fine-tuning of accessible foundation models, enabling excellent performance.

Nevertheless, work on the use of machine or deep learning algorithms in crisis management is focused on very specific tasks, the relevance of which is not always assessed in real time during the occurrence of a crisis whose stakes are always very specific (for example, different floods in different contexts for different responders require the analysis of aerial imagery in different ways). Furthermore, while the multimodal capability of algorithms now makes it possible to broaden the spectrum of types of data processed, the ability to select relevant data for processing and to produce different points of view and level of composing on the same system is not possible under the governance of these AIs.

All these features qualify ML and DL-based systems as ideal candidates for the realization of a SA.

Neuro-Symbolic Approaches

The SA paradigm suits fast individual decision-making, while the Sensemaking paradigm is for groups facing ambiguity, needing collective knowledge, inferences, and diverse perspectives to reach a shared understanding. The translation of this problem to AI is not obvious.

Although not new, neuro-symbolic AI approaches are currently undergoing a revival in tandem with advances in connectionist AI. The temptation is great to hybridize these two approaches in order to benefit from the advantages of each paradigm. Hitzler et al. (2022) notes a second reason for this flourishing, coming directly from the cognitive sciences: "we can understand artificial neural networks as an abstraction of the physical workings of the brain, while we can understand formal logic as an abstraction of what we perceive, through introspection". Wang et al. (2022) exposes the ability of human cognition to juggle 4 dimensions of symbolism and connectionism: Symbols vs Neurons, Deduction vs Induction, Compositionality vs Continuity and System 1 vs System 2. The first two dimensions are fairly common. It is nevertheless important to focus on the other two. *Compositionality vs Continuity Continuity* refers to the sequential activation of neurons in a continuous but variable signal (notably in the "weight" of information circulating) transmitted from neuron to neuron. *Compositionality* refers to the encoding of information in more or less large structures, enabling the generation of composite knowledge representations at variable levels of abstraction. *System 1 vs System 2* Kahneman (2011) proposes that human brain is composed of two conceptual systems. *System 1* is fast and intuitive but can be sometimes imprecise and *System 2* is logical, delibirative and conscious but slower and requires concentration.

In light of this, the literature shows that neuro-symbolic systems are particularly promising for implementing a form of dynamic between the perception of a situation and its understanding according to several levels of composition and expertise in dynamic environment under uncertainties, as required by the Sensemaking's *horizontal* and *vertical* processing of data. Recent articles such as (Booch et al., 2021; Dong et al., 2019) show efforts have been made in this direction. That said, Wang et al. (2022) notes that no hybridization paradigm currently allows us to effectively address the 4 dimensions between symbolism and connectionism sought in the Sensemaking process.

Limits of Current AIs to Meet Information Needs

In conclusion, several observations can be made concerning the state of the art. With regard to the information needs of decision-makers and the improvement of decision-support systems (particularly at this stage of understanding the situation), this is a complex and multifaceted cognitive and human process that is difficult to generalize. It involves coordinating different interpretations at different levels, depending on the scale of the crisis, the expertise involved and the often heterogeneous vocabularies, in a highly dynamic context that is unexpected at each subsequent event.

AI, with its advanced capabilities for processing massive data flows, has become a valuable ally in the development of modules for understanding crisis situations in real time in decision support systems. Symbolic AIs enable logical inferences to be defined and proposed on the basis of a vocabulary established by users, according to their needs. This includes early warning systems: for example, Fertier et al. (2020) offers an expert system based on listening to water level sensors combined with business rules collected from experts in the field (belonging to various institutions such as the Centre for studies and expertise on risks, the environment, mobility and development, Regional Department for the Environment, Planning and Housing, Regional Road Information and Coordination Centre, Interministerial zone headquarters). This type of system proves very effective to infer and confront information when the context of the crisis has already been anticipated and studied (even if it has not yet been encountered in the past), and is based on a strict vocabulary established in advance of the crisis. The dynamic context of the crisis is taken into account as long as the business rules effectively respond to the conditions encountered in real time. Setting up such systems is laborious, not only in algorithmic terms but also time-consuming for the experts, given the complexity of the systems studied. This severely limits the adaptability and realism of such AIs, and shows the need to mix them with more flexible approaches.

ML and DL, by their mechanism of training by past experience, show remarkable capabities for adaptation and generalization, while drastically reducing the demands made on experts. Such systems are extremely useful for reducing the time taken by humans to monitor data, allowing them to devote their attention to tasks linked to the decision-making itself. For example, Suwaileh et al. (2022) offers such an AI dedicated to inferring geolocation of social media posts during a disaster for humanitarian purposes, based on very few data. Unlike an expert system, the AI allows extremely rapid inference, without having to draw up exhaustive lists of potential locations and their grammatical uses (an otherwise unrealistic task). However, these AIs respond to very specific tasks that need to be defined in advance of a crisis and cannot be created on the fly during a crisis, should new types of information prove interesting to extract.

While symbolic AIs make it possible to mimic expert control of the situation understanding process, ML and DL are AIs that are themselves controlled by humans, capable of carrying out tasks flexibly. So, with the aim of establishing AIs close to the needs of the Sensemaking process, neuro-symbolic approaches make it possible to imagine autonomous, flexible and realistic situation understanding modules in future decision support systems.

PROPOSAL

The finding shared by Kautz (2022) and Wang et al. (2022) lies in the promising potential of a neural architecture embedding symbolic reasoning engines, deemed closest to Systems 1 and 2 of Kahneman (2011), to support the Sensemaking process. Whether AI should follow the path of a biological or a non-biological architecture remains a large question. There are however strong beliefs that considering the notable progress of neurosciences, bio-inspired architecture are promising (Hole & Ahmad, 2021).

Neurosciences enable us to better understand these two systems, and most importantly now highlight a so-called inhibition System 3, which plays an executive role in regulating the use of the other two Systems (Houdé & Borst, 2014). This key role makes System 3 the seat of human reasoning, in its ability to question preconceived perceptions and models, and to consider situations both holistically and with subtlety, especially thanks to the ability of meta-cognition given by System 3. However, while we have shown that the AI literature is interested in using the System 1 and System 2 paradigms to propose a hybridization architecture, no proposals have been made for System 3.

This section therefore aims to propose a new high-level integration architecture of a hybrid neuro-symbolic AI inspired by the System 3 allowing both *Compositionality* of the reasoning and *Continuity* of the information flow through neural networks.

We present this proposal in two parts. The first subsection focuses on the observations and theories currently proposed by the neurosciences around three biological subsystems - neurons, cortical columns and distributed inhibition processes - and the roles played by each in levels of human cognition. We use these 3 key biological subsystems to justify our proposal for a neuro-symbolic architecture, set out in the second subsection.

Three Key Biological Sub-Systems for the Human Cognition

In his book *A thousand brains: A new theory of intelligence*, Hawkins breaks down human cognitive capacity into three sub-parts that are found in the human neocortex possessing both *hierarchical - i.e. vertical, in columns -* and *distributed - i.e. horizontal, interaction and voting -* roles.

Neurons

Neurons are the basic building blocks of the human neocortex, transmitting information through impulses. When stimulated, a neuron generates an action potential that travels down its axon, leading to the release of neurotransmitters at the synapse, facilitating communication with other neurons. The structure of neural networks is dynamically influenced by experiences through a phenomenon known as neuroplasticity. When engaging in new situations, the connections between neurons, can be strengthened or weakened. Over time, the observations show that repeated experiences can lead to long-lasting changes in neural pathways, contributing to the continuous evolution of the brain's structure and functionality.

Thanks to their ability to transmit the information in a distributed and loose way, neurons ensure the *Continuity* of the cognitive system. Moreover, the neural map at time t represents the knowledge stored by the individual at this exact instant.

Cortical Columns : One Model Generation

The cortical columns of the neocortex are highlighted by Mountcastle's work in 1957 (Mountcastle, 1957). Cortical columns are sensory-motor systems of the neocortex made up of vertically aligned neurons, all with the same laminar structure and consisting of "functional units of information processing". They perceive data from outside, process it through a back and forth circulation of data and provide specific models of sub-systems of the environment. According to Hawkins et al. (2017), cortical columns "learn complete predictive models of observed objects". Thanks to neural sparse connections between columns, one cortical column can infer models of objects based on the partial knowledge of the adjacent columns, hence ensuring low-level information complementarity in the construction of a model.

The ability of the columns to create atomic models of objects in the environment from individual points of view contributes to the cognitive capacity of *Compositionality*. Models can be closely related to symbolic representations of the environement. Moreover, the ability to inhibit the flow of information from neuron to neuron within the columns at the neuronal level, also associates it with capacities close to those of Kahneman's two systems.

Inhibition and Voting Process : Several Models to One Perception

Mountcastle (1997) observes that columns can also be linked to each other by long-range connections. Hawkins (2021) defends the existence of a voting process by which the thousands of models produced by cortical columns offering different points of view of the same environment can be reconciled into a single, also stable, perception of the environment. These long-range connections enable precisely this process of voting between columns.

Houdé and Borst (2014) describe a comparable inhibition process that associates Kahneman's two systems with a higher-level executive system (meta-cognitive) that is nonetheless clearly distributed within the neocortex. Inhibition System 3 enables us to implement a conscious deductive approach in response to unknown or complex situations.

The regulatory capacity provided by these two complementary theories enables a high-level compromise between *Compositionality Continuity* by reconciling the model of an object underpinning several points of view and levels of submodels, and thereby ensuring cognitive consistency over time. Such higher-level inhibitory system (at a meta-cognition level) is typically not proposed by Hole and Ahmad (2021).

Perspectives for a Bio-Inspired Neuro-Symbolic AI Architecture for Sensemaking Support

Inter-Disciplinary Framework

Figure 3 presents a framework that summarizes and justifies how neurosciences can, through the three levels of neurons, cortical columns and inhibition and voting processes, inspire the creation of AI responding to the very specific informational needs questions demanded by the three paradigms of COP, SA and Sensemaking.

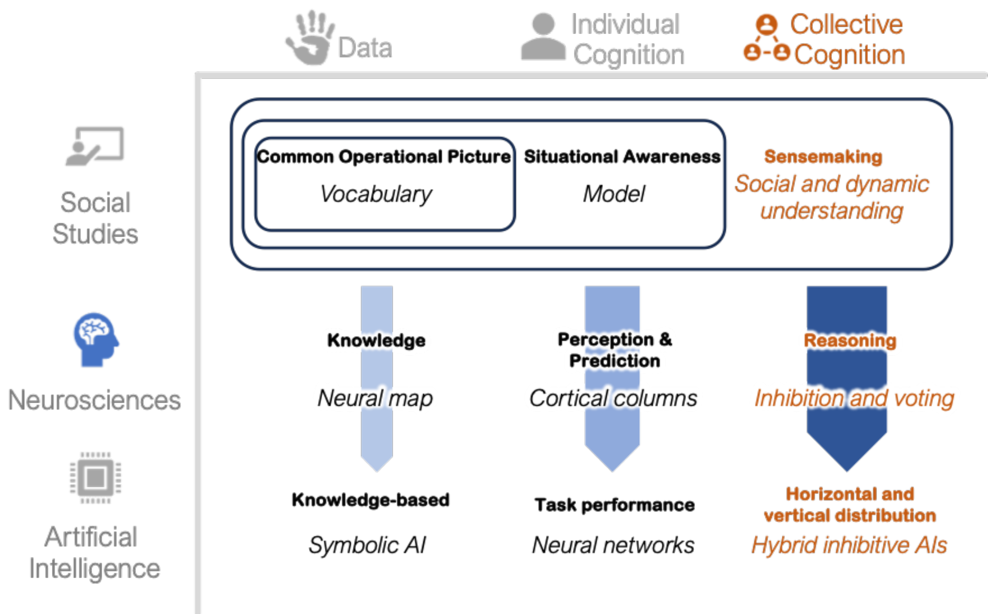

Figure 3. Neuro-sciences as a promising pivot to create new AI aligned with the crisis managers' informational needs.

Bio-Inspired Neuro-Symbolic AI Architecture

Based on neuroscientific observations of human reasoning, we can extract a number of specifications for the construction of a bio-inspired neuro-symbolic AI, capable of embodying the notions of *Compositionality*, *Continuity* and those contained in Kahneman, Houdé and Borst's *Three Systems* and support Sensemaking.

- **Sequencing neural networks within columns**: sequencing neural networks ensures *Continuity* in the flow of information. On the one hand, deeper neural networks enable a complex level of abstraction, by producing more higher-level of aggregation of the input data. In terms of sense Sequencing neural networks thus addresses the *verticality* problem of Sensemaking.
- **Parallelization of columns**: in the same way that cortical columns are used in human cognition as individual computational units enabling atomic models (a point of view, a subsystem - *Compositionality*) of an environment to be established in a parallelized processing process with different data, we propose to parallelize neural networks. The more neural networks there are in parallel, the wider the scope of possible perception by integrating more data sources. In order to share partial models, like adjacent cortical columns, neural connections can be set up between columns. Parallelization of neural networks thus makes it possible to address the *horizontality* problem outlined of Sensemaking.
- **Executive system distributed on two levels**: an executive inhibition system regulates the use of columns on two levels. At a meta-level, a voting process is used to unify the models produced by the columns into a situation model delivered to the crisis manager, thus meeting contextualized information needs. To make this possible, a second process, this time inhibitive, is implemented to regulate the use of columns according to their relevance (i.e. signals perceived from the outside) and the connections between columns. The interest of such an executive system is to ensure coherence between (i) the informational models generated and (ii) the cognitive reasoning implemented within and between the columns. Thus, this executive system is at the heart of the concerns in the development of such an AI architecture: it no longer addresses vertical and horizontal problems independently, but proposes an architecture that is adaptive to needs on both dimensions.

CONTRIBUTIONS, LIMITS AND PERSPECTIVES

This paper makes two contributions: (i) while no AI in the literature is currently capable of supporting the collective cognitive effort made during Sensemaking, current knowledge of the cognitive mechanisms of the human brain observed in neurosciences allows us to propose a pivot between informational needs and the implementation of adapted AIs ; (ii) the proposal of a new AI architecture based on voting and inhibition mechanisms distributed between cortical columns enables us to envisage meta-cognitive capacities capable of supporting Sensemaking in its *horizontal* and *vertical* dimensions (see contributions on Figure 3).

That being said, the proposal remains at its early stage and especially needs further investigations that are the current perspectives of this proposal:

- **Methodologies to better understand mechanisms involved in human cognitive executive system** : current medical imaging techniques do not allow to observe inhibition behaviours at the neuronal level. Hence, very specific experimental methodologies must be implemented to allow a proper control of all parameters and to enable in-depth conclusions to be drawn.
- **Transferring human tests to AI tests**: tests usually carried out by humans to observe their cognitive mechanisms are not directly transferable to AI (for example, the Strooper test - Color-Word Interference Task - requires inhibition on the part of the human, but remains a very simple test for computers).
- **Evaluation of the AI performances** : new measures need to be created to (i) evaluate the predictions generated by this type of AI, given that they would not be dedicated to a single task (ii) and evaluate the added value of this AI according the two-dimensions (horizontal and *vertical*) of Sensemaking.

ACKNOWLEDGEMENT

We acknowledge the use of an AI for translation purposes.

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