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R-IO SUITE: Integration of LLM-based AI into a knowledge management and model-driven based platform dedicated to crisis management

Aurélie Congès · Audrey Fertier · Nicolas Salatgé · Sébastien Rebière · Frederick Benaben

Abstract: This article presents how the R-IO SUITE software platform, a decision support system for Crisis Management entirely based on model-driven engineering principles, considerably benefits from large language model (LLM) based artificial intelligence (AI). The different components of the R-IO SUITE platform are used to climb the four abstraction layers: data, information, decision, and action through interpretation (from data to information), exploitation (from information to decision), and implementation (from decision to action). These transitions between layers are supported by a knowledge base embedding knowledge instances structured according to a crisis management metamodel. From a functional perspective, this platform is fully operational, however, to be able to cover any type of crisis situation, the knowledge base should be enriched, first, from a “resource perspective” (to embed the various available means to deal with any faced situation), and second, from an “issue perspective” (to understand all risks and damage that can appear on a crisis situation). It is not reasonable to consider creating and maintaining such an exhaustive knowledge base. However, the connection of the R-IO SUITE platform with LLM software such as ChatGPT© makes it possible, by generating appropriate prompts, to update on-the-fly the knowledge base according to the faced context. This article shows how the LLM AI can provide complementary knowledge to formally fulfill the knowledge base to make it relevant to the faced crisis situation. This article presents the R-IO SUITE as a LLM-empowered model-driven platform to become an extended crisis management supporting system.

Keywords: Large Language Model, Artificial Intelligence, Model-Driven Engineering, Decision Support System, Knowledge base, Ontologies, Metamodel, Complex Event Processing, Business Process Management.

1. Introduction

According to (Alexander, 2002; Cutter, 2003), crisis management is traditionally

structured around four phases:

- The *prevention* phase to ensure that the crisis does not occur;
- The *preparation* phase to ensure that we are as ready as possible to respond to the crisis;
- The *response* phase to return to an acceptable, controlled state by implementing the measures planned in preparation, combined with any complementary ad hoc measures;
- The *recovery* phase to return to a satisfactory state in the long term.

In reality, the *prevention* phase continues throughout all the other phases, in particular to avoid over-crisis phenomena. There is a fairly significant compartmentalization between the activities linked to the four phases mentioned, except for the *preparation* and *response* phases, which are closely linked. In fact, the *preparation* phase is mainly concerned with organizing the means to react, in the *response* phase, to the feared events, while the *response* phase is essentially concerned with implementing the capabilities resulting from the *preparation* phase. This article focuses on these two phases of *preparation* and *response*, and in particular on the technological support that can be provided.

In the field of crisis management, and more generally of situational agility, the main ambition schematically concerns the continuous implementation of the following two capabilities:

1. *Ability to perceive* reliably the situation encountered (*i.e.* create a trustworthy and accurate perception of the observed situation):
 - in the *preparation* phase, to identify available skills and resources;

- in the *response* phase, to assimilate available data.
2. *Ability to plan* an effective response to the situation (*i.e.* build response scheme(s) appropriate to the situation encountered, but also to the resources available):
- in the *preparation* phase, to identify the disturbances that may be encountered;
 - in the *response* phase, to define appropriate response schemes, coordinate the skills identified to deal with the situation encountered.

These two stages (i) enable to build a *knowledge repository* describing the resources available and the potential problems encountered (instantiation of the ontology of a knowledge base). The two stages (ii) correspond to the use of this *knowledge repository* to model the actual situation encountered.

Emergency decision support systems are designed and developed to support the response to a crisis. Among them, R-IO SUITE, including its virtual reality overlay R-IO VR, is an open source research prototype (Conges et al., 2023; Fertier et al., 2021, 2020). It enables emergency managers to automate their perception of elements of their environment, improve their comprehension of the ongoing events and support decision-making. Thus, R-IO SUITE is designed to improve their situation awareness, as defined by (Endsley, 1988) in near real-time.

Given the unpredictable nature of crisis, such emergency decision support systems depend on the extent of their knowledge base to adapt their decision support to unexpected events. In addition, an exhaustive population of a knowledge base for a type of crisis (*i.e.* flood) is heavily time consuming and realistic only in strictly defined and thus restricted thematical domain. These knowledge bases are based on feedback of past events, human expertise or on official documentations. Thus, they are not made to fit unexpected type of crisis, such as Fukushima (2011) or COVID-19.

Ontologies (Gruber, 1993) and metamodels (Chen et al., 2008) serve as formal, explicit descriptions of the concepts used in information systems. They harmonize syntax and semantics to formalize, store and interface knowledge, thus improving interoperability between information systems. (Madni and Sievers, 2018) advocates model-based engineering approaches to place models at the heart of information system development.

Advances in artificial intelligence, and in particular in machine learning, have enabled research on the automated population of ontologies, metamodels, and, more generally, knowledge bases, thanks to various inputs (texts (Chasseray et al., 2023), images, or even videos). As fully described by (Zhao et al., 2023), language models have evolved from specific task helpers in the 90s to today's general-purpose task solvers capable of handling various real-world tasks. Zhao et al. (2023) present the application of LLM in healthcare, education, law, finance, and even scientific research. Emergency decision support systems need 'n' types of tasks to get the information their users need. One modern LLM, such as GPT 3 or 4, ChatGPT®, Claude or Llama, can replace 'n' task solver. They can be used to generate structured knowledge, from unstructured input (texts or images) that would be able to fill, on demand, the void left by prepared emergency knowledge base. In addition, few shots prompting (Ye and Durrett, 2022) can be used to fine-tune the output of the LLM.

The question this article proposes to answer is the following: ***Can emergency decision support systems benefit from LLMs to adapt their (i) knowledge base and adapt (ii) their decision support to unexpected events?***

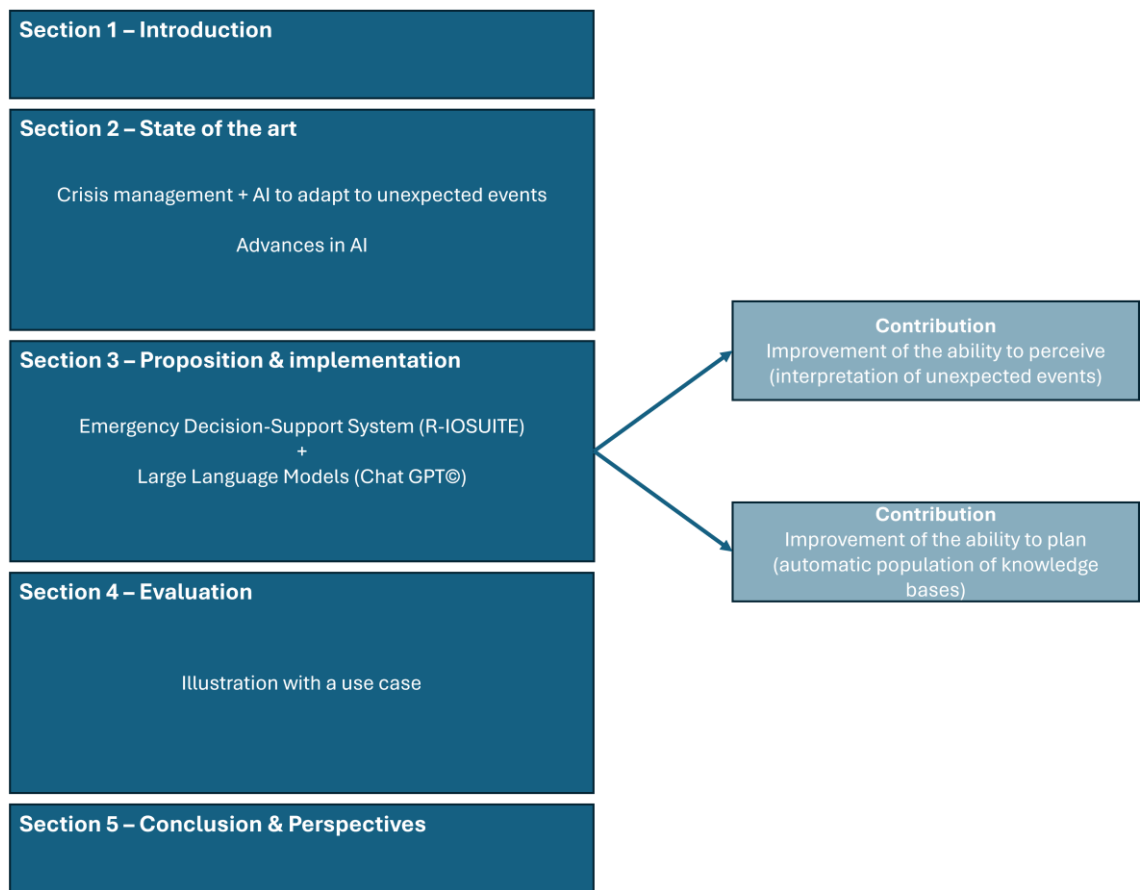


Figure 1 - Methodology followed by this research work

Figure 1 illustrates the methodology addressing this question. Section 2 seeks information systems or decision support systems dedicated to crisis management and able to adapt to unexpected events through the real-time interpretation of data. Existing tools focus on either the preparation phase or the response phase, and none but one of them proposes to use LLM. Section 3 shows how LLMs can be used at both preparation phase and response phase to improve emergency decision-support. It is illustrated with the implementation of **ChatGPT** on the R-IO SUITE prototype to improve both its *ability to perceive (thus adapting the knowledge base)* or its *ability to plan (thus adapting the decision support)*. Section 4 delivers an evaluation of the obtained R-IO SUITE platform implementing LLMs on a case study: an attempted break-in at a research facility. Finally, **Section 5** concludes with future avenues for other uses of LLMs in crisis management.

2. State of the art

A literature review was carried out on the *Scopus* and *Web Of Science* database on the 12th of February 2024. Query 1 presented below returned 2 documents from the same research team (L. Wang et al., 2023; Z. Wang et al., 2023).

(1)	((crisis OR emergency OR disaster OR "civil defense") W/1 (management OR preparation OR response))
(2)	"large language model*" OR "pre-trained language model"
(3)	"ontolog*" OR "metamodel*" OR "formal knowledge" OR "semantic net*" OR "semantic network*" OR "knowledge graph*" OR "knowledge representation"

Query 1 - Query run on the WebOfScience database the 12 February 2024

To broaden the scope of our research, query 2 presented below searches for all documents, in the computer science area, presenting (1) an information system or decision support system dedicated to emergency management and able to (2) assimilate data to (3) update a knowledge base or a situation model.

(1)	((crisis OR emergency OR disaster OR "civil defense") NEAR/1 (management OR preparation OR response))
(2)	(((data OR event* OR text* OR image* OR video* OR language) NEAR/2 (processing OR driven OR fus* OR assimilat* OR interpret*))) OR ((information OR knowledge) NEAR/2 (extract* OR acqui* OR retriev*))
(3)	"ontolog*" OR "metamodel*" OR "formal knowledge" OR "semantic net*" OR "semantic network*" OR "knowledge graph*" OR "knowledge representation"

Query 2 - Query run on the WebOfScience database the 12 February 2024

Query 2 returned a corpus of 96 documents, including (L. Wang et al., 2023). Thanks to the bibliometrix package (Aria and Cuccurullo, 2017), we studied the author keywords, keywords plus, abstracts, and references of the corpus. Among the references most cited by the corpus, cited by at least 5 of the 96 documents, we found: (Gruber, 1993) for his definition and research work on ontologies, cited by 12% of the corpus; (Amailef and Lu, 2013) for their work on case based reasoning; (Endsley, 1995) for her work on situation awareness and human decision making; (Cheng et al., 2017; Li et al., 2014) for their work

on indoor localization during a fire-fighting operation thanks to the BIM of the building and metaheuristics; (Studer et al., 1998) for their review of knowledge engineering principles and methods. The author's keywords referring to ontologies, knowledge graphs, or the semantic web are the most present in the corpus. This seems to indicate that the corpus agrees on the goal: instantiate or improve a knowledge base for better decision support, but not on the mean: how to assimilate data or acquire information or knowledge?

Of the 96 documents, 20 are articles, with a DOI, classified in the field of *computer science* and published after 2015. Among them 10 articles do not use data to update a knowledge base, a metamodel or an ontology: (Scherp et al., 2012) propose a core ontology to represent events and relationships between events; (Amailef and Lu, 2013) propose an emergency decision support system to easily retrieve past cases in a knowledge base; (Ilyas, 2015) proposes a domain ontology of natural and made events; (Zhang et al., 2015) propose to improve the query performance of geospatial ontologies; (Lee et al., 2017) do not apply their research on emergency management; (Botega et al., 2017) propose a methodology to assess the quality of information contained in a situation model; (Santos et al., 2019) propose a topology of adverse events driven by the effects, rather than the causes; (Kemavuthanon and Uchida, 2020) propose an emergency decision support system able to answer the questions of its Japanese users; (Mughal et al., 2021) propose a domain ontology for flood management; (Berger et al., 2023) propose a system to synchronize knowledge inside a team of robots.

Table 1 lists the other articles that use data to update a knowledge base, a metamodel, or an ontology. The resulting 10 articles are in rows. When they concern the same research teams, the articles have been grouped on the same row. This concerns the work of (Ahmad et al., 2019, 2017), (Fertier et al., 2021, 2020) and (L. Wang et al., 2023;

Z. Wang et al., 2023). The first column shows the article reference. Columns 2 to 6 (Name, Input, Pipeline, Output, Scope and Case study) respectively present the name of the proposed system or method, the type of data used to update the knowledge base, the pipeline used to process the data, the output, the scope of the research work, and the case study used to demonstrate it.

Table 1 - Results of the literature review on articles presenting an information system or decision support system dedicated to emergency management and able to assimilate data to update a knowledge base or a situation model¹.

	Name	Input	Pipeline	Output	Scope	Case study
(Poslad et al., 2015)	IoT EWS	Message	KB, O, DF	Impact	Early warning	Tsunami
(Othman et al., 2016)	DMKR	Past crises	KB, MM	Instances	E. planning	Bushfire
(Qiu et al., 2017)	FDMS	Flood data and images	O, DF	Data view	Flood	Ganjiang River
(Ahmad et al., 2017)	SSW	Tweets in Urdu	O, NER	Instances	N/A	Pakistan
(Sene et al., 2018)		Observations	O, DM, KB	Instances	Medical incident	N/A
(Fertier et al., 2020)	R-IO SUITE	Sensor and open data	CEP, KB, MM	Instances	E. management	EM
(Karthikeyan et al., 2023)	IoT EWS	Message	KB, O, DF	Impact	Early warning	Tsunami
(Wang et al., 2023)	PTM MCNN	C. Plans	PTM, NN, NER, KG	C. Plan	E. planning	River diversion

All the methods or systems of Table 1 focus on either the preparation phase (Othman and Beydoun, 2016; Sene et al., 2018; L. Wang et al., 2023) or the response phase of crisis management (Ahmad et al., 2017; Fertier et al., 2020; Karthikeyan et al., 2023; Poslad et al., 2015; Qiu et al., 2017). In particular, (L. Wang et al., 2023; Z. Wang

¹ Abbreviations: IoT internet of things; KB knowledge base; O ontology; DF data fusion; MM metamodel; DM data mining; E emergency; CEP complex event processing; PTM pre-trained language model; NN neural networks; NER Named entity recognition; KG Knowledge graph; RE

et al., 2023) use pre-trained language models (PTM) to perform entity recognition on their textual inputs, specifically emergency plans. This enables them to automatically populate a knowledge base with these procedures during the preparation phase. The research work presented in this paper aims to go further by using LLMs not only in the preparation phase but also in the response phase to update the knowledge base supporting decision-making.

As a conclusion, and given the scope of this literature review, the main takeaway is that there is no research work on how to update a knowledge base, before and during a crisis response, thanks to a pretrained LLM. This opens the door to a new usage of LLMs for knowledge base instantiation. The following sections introduce how R-IO SUITE, augmented with an LLM, **ChatGPT©**, provide a more accurate and extended service in both the preparation phase and response phase of crisis management.

3. On the use of **ChatGPT© for on-the-fly model instantiation in R-IO SUITE**

R-IO SUITE is a model-based software prototype developed from over fifteen years of research and scientific contributions, starting with (Bénaben et al., 2008). It has undergone a significant transformation due to advances in LLM-based artificial intelligence. This section outlines the main principles of the R-IO SUITE prototype platform, including its structural limitations, and describes the recent features added through interaction with **ChatGPT©**.

3.1. R-IO SUITE main principles and features

R-IO SUITE includes a metamodel, a knowledge base structured by the metamodel, mechanisms to create context-aware metamodel-compliant models from external data streams, mechanisms to transform models, and mechanisms to send information, such as decisions or notifications.

metamodel concepts to be instantiated. The *situation model* obtained, a common operational picture as defined in (Steen-Tveit and Erik Munkvold, 2021), is constantly updated to follow the dynamic of the crisis situation.

- [DECISION-SUPPORT ‘ability to plan’] ***The exploitation level supports decisions.*** It uses model-transformation principles to create a response model respecting doctrinal principles (Bénaben et al., 2016), thanks to the knowledge base, including the current *situation model*. R-IO SUITE evaluates the syntactic and semantic similarities between the situation model and the knowledge base to link the objectives to be achieved and the capabilities of the available stakeholders. If no link is possible, then the objective or function remains orphaned. The response model proposed is submitted to the emergency managers using R-IO SUITE for validation to keep the human in the loop.
- [EXECUTION] ***The implementation level supports acting on decisions.*** It uses a workflow engine to execute and monitor the response model. Applications and services can be invoked thanks to a service-oriented architecture and human actors can be notified and acknowledge the achievement of their tasks thanks to the R-IO 4U mobile application. During the implementation, interpretation and exploitation are continuously ongoing, to ensure that any changes, developments or disturbances are detected, to adjust the implemented response schemas (Barthe-Delanoë et al., 2018, 2014).

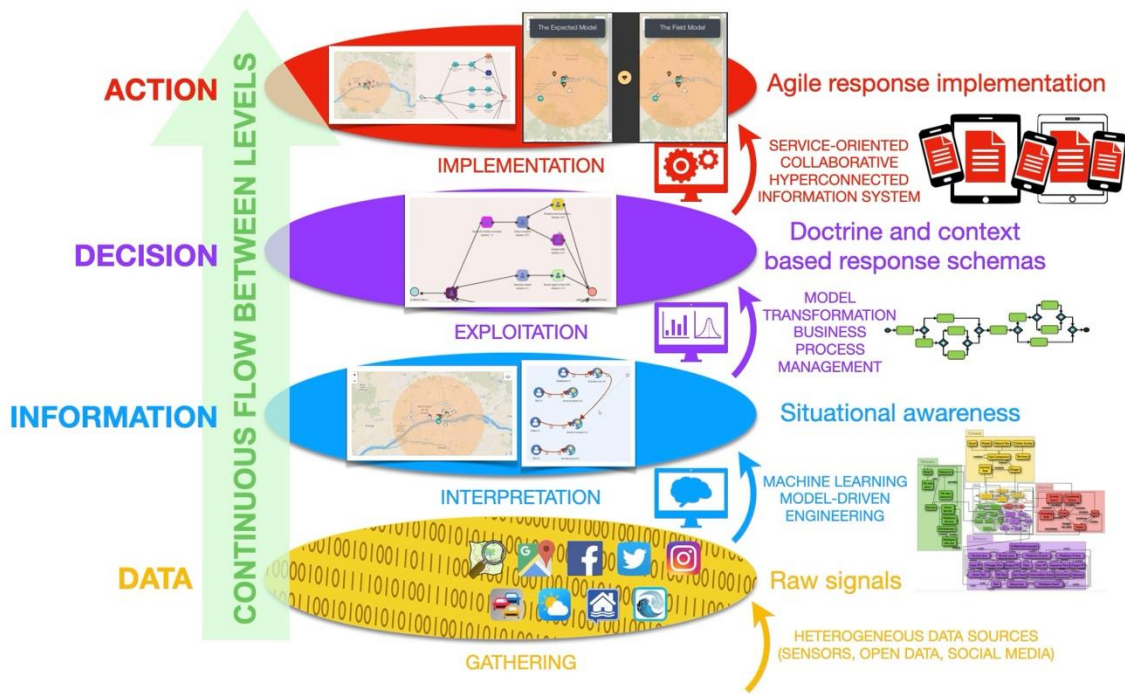


Figure 3. Big picture of the R-IO SUITE framework.

These four transitions are supported by a transversal knowledge base structured according to the COSIMMA metamodel (Benaben et al., 2020), which is dedicated to crisis collaboration modelling. Figure 4 illustrates the COSIMMA metamodel. It is composed with CORE concepts and relationships, as well as domain concepts and relationships related specifically to crisis management. It is structured by four packages:

- *The context package* in yellow, to model the crisis site;
- *The partners package* in green, to model the stakeholders, their capabilities and their of resources;
- *The objectives package* in red, to model the risks to be prevented and the damages to be treated. For example: the risk "risk of explosion in building A" leads to the creation of the objective "prevent the risk of exposure in building A", or the fact "fire in building A" leads to the creation of the objective "treat the fire in building

A".

- *The behavior package* in purple to model the collaborative response scheme. It is inspired from the BPMN language.

The *gathering level* from Figure 3 gathers data which are not modeled in the knowledge base. The *interpretation level* instantiates concepts and relationships of the COSIMMA metamodel to update the situation model part of the knowledge base. To climb the *exploitation level*, for each objective of the situation model, R-IO SUITE selects, in both the *partners and objectives packages* (Truptil et al., 2010): (i) the *closest objective* from the knowledge base, based on semantic links implemented with the 'near' relationship; (ii) the *most suited function* from the knowledge base to process the *closest objective*; and (iii) a *function from the situation model*, 'near' the *most suited function*, as well as its pre-requisites and post-requisites in line with official procedures. For example, to address a fire in Paris, it selects (i) "treat the fire in building A"; (ii) "extinguish a building fire"; and (iii) the function "extinguish a fire" proposed by the Paris fire service. The selected *functions from the situation model*, along with its pre-requisites and post-requisites, are modeled in a *proposed response scheme*, instantiating the *behaviour package*, by using optimization algorithm and taking into account resource mobilization conflicts. Finally, the *implementation level* uses the *behaviour package to transform the response scheme model into an instance of a workflow*.

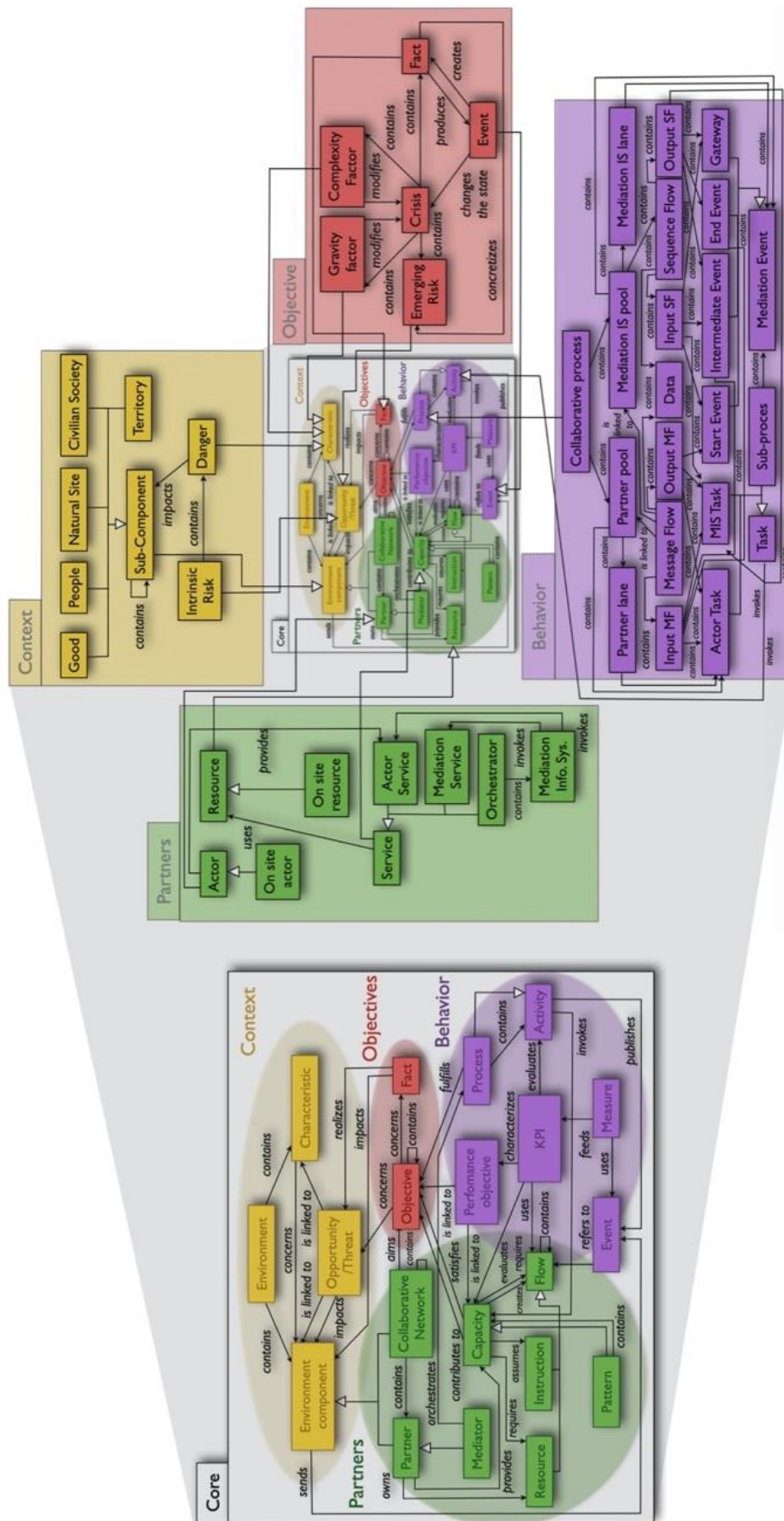


Figure 4. The COSIMMA crisis management metamodel.

3.2. R-IO SUITE limitations and the associated proposal

From a functional perspective, the R-IO SUITE platform is fully operational as it has been widely documented (Barthe-Delanoë et al., 2014; Benaben et al., 2020, 2019; Bénaben et al., 2016; Fertier et al., 2020), but this theoretically operational platform has significant limitations, particularly in terms of coverage.

3.2.1. Limits of R-IO SUITE

Not long ago, as underlined in several literature review, or the automatic, and rapid, extraction of information from (i) data streams (Fertier et al., 2021, 2020), (ii) social media (Coche et al., 2021), or (iii) open geographical information systems (such as Open Street Map), was made possible by the use of machine learning, or complex event processing. (Coche et al., 2021; Fertier et al., 2020) use them to respectively filter tweets, or data streams, respectively enrich them or contextualize them, in order to finally, update the knowledge base, in both an *issue perspective*, i.e. the common operation picture (as defined in (Steen-Tveit and Erik Munkvold, 2021)), and a *resource perspective*, to embed the various available means to deal with the faced situation

Applied to crisis management, complex event processing engines rely on a set of rules, which can be given by experts, feedback of past events, or existing (Barthe-Delanoë et al., 2018). For example, the following business rule can be implemented: *if the water level in the river exceeds 5m at point X, and it rains less than 2 km upstream, then an instance of the risk concept is created with the heading "flood risk at point X"*. Like the knowledge bases, an exhaustive set of rules will be dedicated to both a type of crisis (i.e. flood), and a set of data streams (i.e. water levels), will be heavily time consuming and realistic only in restricted set of data sources. Thus, they will never fit unexpected crisis evolution, such as Fukushima (2011).

Applied to crisis management, machine learning models, as well as neural network models, rely on large amount of labeled data (Coche et al., 2021), and are trained on specific tasks. Like the knowledge bases, and the complex event processing rules, the large amount of labeled data will never fit all unexpected crisis evolution. LLMs, such as ChatGPT© or Llama, have already been trained. Given a prompt, they adapt their output to any kind of structure (metamodel or ontology).

3.2.2. General proposal to address the previously described limitation

R-IO SUITE can integrate LLMs and generate appropriate prompts to augment its knowledge base on-the-fly in response to crises and their unexpected evolutions. With LLM integration, R-IO SUITE becomes a powerful model-based platform, paving the way for an emergency decision support system extendable to any kind of crisis.

Figure 5 summarizes the architecture of the two components of R-IO SUITE augmented with LLM integration. It illustrates the augmented ‘ability to perceive’ data streams and information coming from open data, social media, sensors, text messages or images. They are either assimilated via the complex event processing engine, for quantified, structured data streams, or LLM, for unstructured data. The same LLM is used by the augmented ‘ability to plan’. The *low level interpretation* assimilates data, while the *high level interpretation* instantiates the COSIMMA concepts and relationships. These two uses are illustrated in the lower part of the figure and describe in the two following subsections.

The integration of LLMs into R-IO SUITE required two full-time engineers, following a DevOps approach, working for two months on the initial version. This version is regularly maintained as libraries and LLMs evolve, with a new release scheduled every six months. We also pay to access the openAI API, which granted us access to ChatGPT©. The version used at this stage is ChatGPT©-4. The cost depends on the volume of usage.

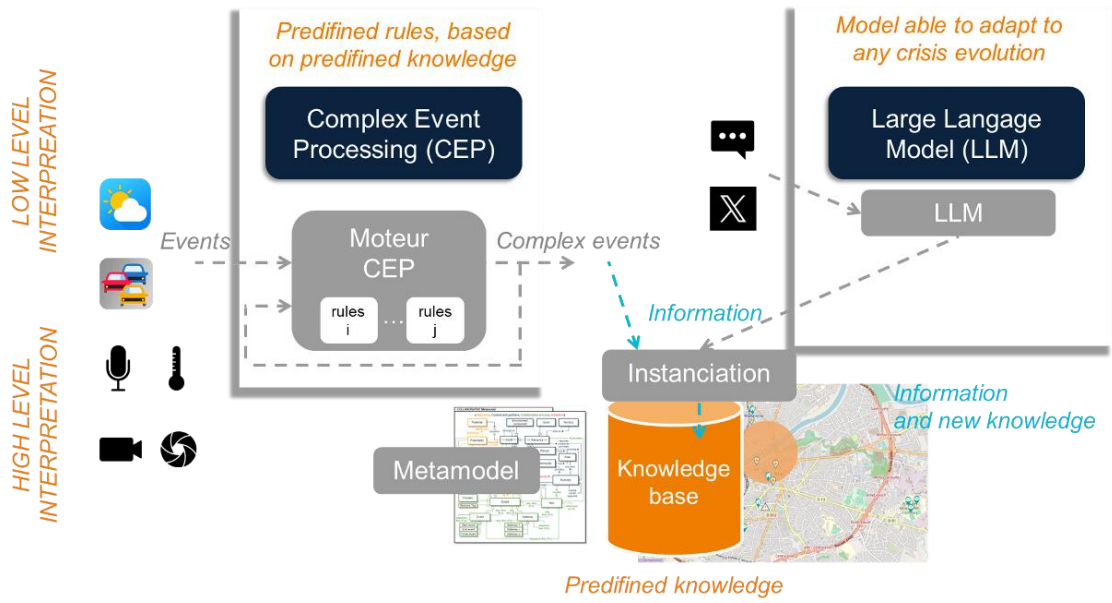


Figure 5 - The architecture summarizing the contribution of this paper

3.3. The use of LLM to augment the comprehension level of R-IO SUITE: “ability to perceive”

3.3.1. The use of LLM to identify actors

Perception: ability to perceive

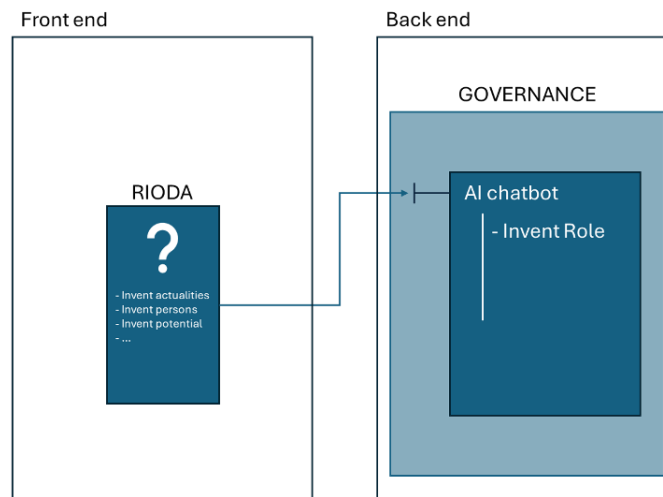


Figure 6 - View of the modules in charge of the 'ability to perceive'

Figure 6 shows how R-IO SUITE enables its users to ask for a new role to be added to their knowledge base. This functionality is available via the R-IODA (*Design Assistant*) application. It is used in situations involving actors whose role are not yet known in the knowledge base. The function “inventRole” send a predefined query to a LLM to obtain a list of functions that this type of actor is likely to perform, as well as the associated pre-required and post-required functions. This query is carried out in two stages:

1. It asks a LLM for the set of functions associated with an unknown role (below is the request for a "firefighter" and the response obtained):

```
Query:
For each role in this array: [firefighter], give me its associated functions
with these data: { role: "role", functionsOfRole: [ { the name of the function
(name=string), the description of the function (description=string),
satisfaction_level in percentage (satisfies=number)} ] in a valid json array
format (avoid to forget double quotes for string) ?
```

```

JSON Response:
[
  {
    "role": "firefighter",
    "functionsOfRole": [
      {
        "name": "Extinguish Fires",
        "description": "Responding to fire incidents and using equipment to extinguish fires to protect lives and prevent property damage.",
        "satisfies": 95
      },
      {
        "name": "Perform Rescues",
        "description": "Saving individuals from dangerous or life-threatening situations, such as from burning buildings or crashed vehicles.",
        "satisfies": 90
      },
      {
        "name": "Provide Medical Services",
        "description": "Offering first aid and basic medical support at the scene of an emergency before the arrival of medical professionals.",
        "satisfies": 85
      },
      {
        "name": "Conduct Fire Prevention Analyses",
        "description": "Inspecting buildings and environments to identify fire hazards and advising on how to reduce risks.",
        "satisfies": 80
      },
      {
        "name": "Maintain Equipment",
        "description": "Regularly checking and maintaining firefighting equipment to ensure it is functional and ready for use when needed.",
        "satisfies": 75
      },
      {
        "name": "Train and Educate",
        "description": "Participating in regular training exercises to stay up-to-date with firefighting techniques and educating the public on fire safety.",
        "satisfies": 88
      }
    ]
  }
]

```

Query sent to a LLM, here [ChatGPT](#), for the firefighter role and answer

2. It asks the same LLM for all the pre-required and post-required functions for all the identified functions (below is the request for the functions returned for the "fireman" and the response obtained):

```

Query:
For each main function: [{ functionName: "Extinguish Fires", functionId:

```

```
"funct_4ed88344-6844-4577-bc50-d6e7f020a263" , jobName: "Firefighter" }],  
Imagine the actions that should be done as a prerequisite (if you can find any),  
the actions that should be done as a postrequisite (if you can find any) and the  
actions that should be done in parallel (if you can find any)(The output must  
be formatted in a valid json array like that: [{ functionId: "functionId",  
functionName: "functionName", prerequisites?: [ { functionName (string),  
description (string), jobName (string=The same jobName of the main function or  
another name such Policeman, Physician) ], postrequisites?: [ { functionName  
(string), description (string), jobName (string=The same jobName of the main  
function or another name such Policeman, Physician) } ] ], parallelActions?: [ {  
name (string), description (string), jobName (string=The same jobName of the  
main function or another name such Policeman, Physician) } ] ] ) ?
```

JSON Response:

```
[  
  {  
    "functionId": "funct_4ed88344-6844-4577-bc50-d6e7f020a263",  
    "functionName": "Extinguish Fires",  
    "prerequisites": [  
      {  
        "functionName": "Assess the Situation",  
        "description": "Evaluate the scale, type, and specifics of the fire and  
the environment to decide on the best approach.",  
        "jobName": "Firefighter"  
      },  
      {  
        "functionName": "Ensure Safety",  
        "description": "Secure the area and ensure that people are evacuated to  
prevent injury or loss of life.",  
        "jobName": "Firefighter"  
      },  
      {  
        "functionName": "Establish Water Supply",  
        "description": "Set up a reliable water source to be used for  
extinguishing the fire.",  
        "jobName": "Firefighter"  
      }  
    ],  
    "postrequisites": [  
      {  
        "functionName": "Overhaul",  
        "description": "Check for remaining hot spots or hidden embers to prevent  
rekindling.",  
        "jobName": "Firefighter"  
      },  
      {  
        "functionName": "Begin Investigation",  
        "description": "Initiate an investigation to determine the cause of the  
fire.",  
        "jobName": "Fire Investigator"  
      },  
      {  
        "functionName": "Report Incident",  
        "description": "Complete necessary paperwork and reports about the fire  
incident.",  
        "jobName": "Firefighter"  
      }  
    ]  
  }  
]
```

```

    }
  ],
  "parallelActions": [
    {
      "name": "Communicate with Team",
      "description": "Use radios and signals to coordinate actions and share
critical information among team members.",
      "jobName": "Firefighter"
    },
    {
      "name": "Traffic Control",
      "description": "Control and redirect traffic around the emergency scene
for the safety of the public and first responders.",
      "jobName": "Policeman"
    },
    {
      "name": "Provide Medical Assistance",
      "description": "Attend to any injuries sustained by civilians or
firefighters during the operation.",
      "jobName": "Paramedic"
    }
  ]
}
]

```

Query sent to a LLM, here **ChatGPT** for the fireman role and answer

These two steps can be performed with any language model accessible through the use of the langchain4j package (<https://docs.langchain4j.dev/>), such as Anthropic, PaLM 2, JLLama, and OpenAI (including its **ChatGPT**). The package adapts both the input and output to the different LLMs' APIs.

These instances are not added to the 'permanent' part of the knowledge base. For example, in the event of a fire in the Louvre Museum, the Louvre Museum security guards, specific to the Louvre Museum, could have duties related to evacuating people and works of art. If added to the knowledge base, through the *'inventRole'* function, they will not be added to the 'permanent' knowledge base that could be used in the event of a fire in another museum or another critical infrastructure.

3.3.2. The use of LLM to identify new risks and facts

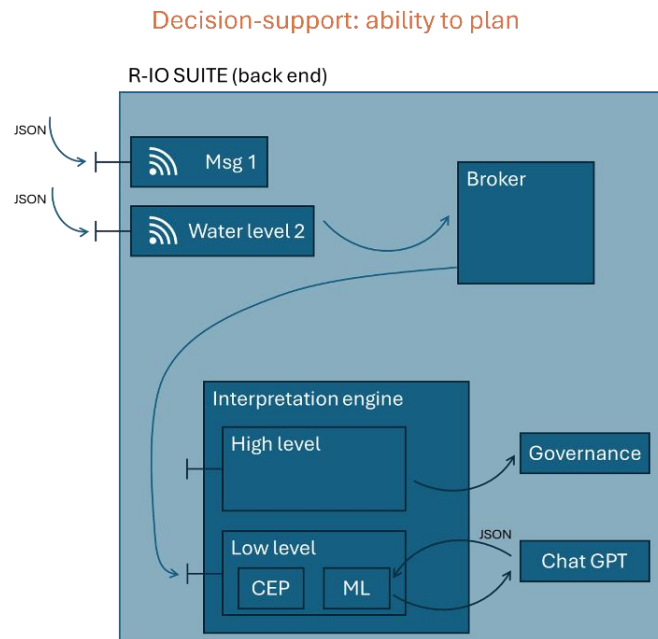


Figure 7 - View of the modules in charge of the 'ability to plan'

Figure 7 shows how R-IO SUITE implements the *perception and interpretation levels* from Figure 3. The *low level and high level interpretation* modules are the one illustrated in Figure 5. Upstream, they are linked to a broker, translating messages, linked itself to the modules listening to each data source known by R-IO SUITE. Downstream, they are linked to both a CEP, when expert rules are available, and ChatGPT©.

The emergency managers using R-IO SUITE can add any data source they want to listen to via the R-IORED application. They are four predefined types of data sources:

- *Dedicated sensors* (boolean input), such as intrusion sensor, associated with a predefined fact accessible in the 'permanent' knowledge base. If the input changes from 0 to 1, this fact is added to the situation model;
- *Quantitative sensors* (float input), such as water level sensor, associated with a threshold rule and a predefined fact accessible in the 'permanent' knowledge base.

If conditions are verified, this fact is added to the situation model;

- *Social sensor* (textual input), such as tweets or messages coming from the R-IO SUITE's mobile application, R-IO4U;
- *Media sensor* (image input).

The structured data streams coming from dedicated sensors and quantitative sensors are interpreted through the CEP engine (see Section 3.1). The unstructured data coming from social and media sensors are interpreted through an LLM via langchain4j. We chose to use **ChatGPT** by default because it was technically easier to subscribe to and more performant than the others. Below is a message from a *social sensor* comprising text and an image.

```
{
  "date": "2024-01-25T14:43:52.169",
  "sensorEventIndex": 0,
  "data": {
    "social": {
      "value": {
        "message": {
          "msgUser": {
            "id_str": "14",
            "name": "Henri Hubert"
          },
          "text": "Help !!! someone is feeling
unwell!!!",
          "media": [
            {
              "type": "photo",
              "url":
https://cdn.dimsumdaily.hk/wp-content/uploads/2021/07/29124307/Screenshot-2021-07-29-at-12.42.32-PM.png
            }
          ]
        }
      }
    }
  },
  "sensorNature": {
    "socialNature": "MESSAGING"
  },
  "sensorType": "SOCIAL",
  "collaborationName": "R-IO Suite",
  "position": {
    "point": {
      "latitude": 33.8636,
      "longitude": -118.260515
    }
  },
  "knowledgeSpaceName": "Barbecue",
  "sensorId": "node_0e852dc6-241c-4e08-adfa-3aa8d9429b9f",
  "eventId": "2"
}
```




Figure 8. Received image from a social media (source: <https://www.dimsumdaily.hk/>).

Following the reception of this event (text and image), the following query is sent to **ChatGPT**:

```
{
  "messages": [
    {
      "role": "system",
      "content": "You are a crisis management assistant. All your responses must be in the form of a valid json as desired by the user"
    },
    {
      "role": "user",
      "content": [
        {
          "text": "Do you detect if there is a danger and risks in this sentence: \"Help !!! someone is feeling unwell!!\" and in the image attached to the request and if yes, identify them by specifying your certainty index (avoid doublon) (if no, return empty json array) ?(The output must be a valid JSON array of the following form: [ { type: enum(\"risk or danger\"), name: \"name of a danger or a risk\", certainty_index: number (between 0 and 1), probability_that_risk_occurs: number (between 0 and 1 if type = risk) } ]))",
          "type": "text"
        },
        {
          "image_url": {
            "url": "https://cdn.dimsumdaily.hk/wp-content/uploads/2021/07/29124307/Screenshot-2021-07-29-at-12.42.32-PM.png"
          },
          "type": "image_url"
        }
      ]
    }
  ],
  "model": "gpt-4-vision-preview"
}
```

R-IO SUITE then gets the following response from **ChatGPT**:

```
[
  {
    "type": "danger",
    "name": "Medical emergency",
    "certainty_index": 0.9
  },
  {
    "type": "risk",
    "name": "Public safety risk due to medical emergency",
    "certainty_index": 0.7,
    "probability_that_risk_occurs": 0.6
  }
]
```

Once validated by a user, each of these instances are added to the situation model. This manual validation concern only those of informational interest for crisis management or by requests for confirmation by other means, such as the request for a complementary report by an actor on site.

3.4. The use of LLM to augment the exploitation level of R-IO SUITE: “ability to plan”

The *exploitation level* of R-IO SUITE aims to propose a *response scheme* by associating available *functions* to *goals* to be satisfied, all modeled on the situation model (see Section 3.1). For each goals without available functions to satisfy them, emergency managers can use the “inventRole” function of R-IO SUITE (see Section 3.3.1) to ask for new roles, goals, or functions; R-IO SUITE can ask what functions could address an orphaned objective, or what types of actors could be able to perform some functions. Below you can see the query submitted for a building damage prevention objective and the ChatGPT’s response:

```
Query:
For each problem in this array: [{"problemName":"Prevents Infrastructure
Damage","problemId":"obj_edccb88-6646-4d79-9533-746dcb1e2be0"}], can you
identify which job and which associated only one function that could satisfy
this problem (the output should be a valid json array of the following form:
[{"jobName": string, jobFunctions: [ { jobFunctionName: string, problemName:
string, problemId: string } ]])?
```

```
JSON Response:
[
```

```

{
  "jobName": "Civil Engineer",
  "jobFunctions": [
    {
      "jobFunctionName": "Infrastructure Design and Analysis",
      "problemName": "Prevents Infrastructure Damage",
      "problemId": "obj_edccbc88-6646-4d79-9533-746dcb1e2be0"
    }
  ]
}
]

```

Query from R-IO SUITE for building damage prevention objective and answer from [ChatGPT](#)

R-IO SUITE can then (i) assign these functions to existing actors, even if they are not initially qualified to perform them (forcing), or (ii) look for backup actors who are qualified to perform the requested functions, and integrate them into the knowledge base.

3.5. LLM's contribution to the R-IO SUITE model-driven platform

The use of a LLM enables the model-driven platform to rely on a *variable geometry knowledge base* whose content adapts in real-time to the situation encountered and the platform's functional requirements. It is structured according to a metamodel: the COSIMMA metamodel common to all application cases. This *variable geometry knowledge base* constitutes the core of our contribution. It enables dynamic improvement of the knowledge base, leading to better situational and contextual awareness, as well as better decision support (i.e. better response schemes proposed to emergency managers).

4. Demonstration of the AI-augmented R-IO SUITE platform

This section focuses on the demonstration of the R-IO SUITE platform augmented by [ChatGPT](#) in a crisis management context.

4.1. Crisis managements characteristics and needs

A crisis begins when the fundamental structures, values and norms of a system are threatened (Devlin, 2006; Lagadec, 1994; Rosenthal and Kouzmin, 1997). During a

crisis response, emergency managers face moments with no information, as well as times when everything happens at once (Lagadec, 1994).

“The ‘thing’ is there, in full size or, perhaps worse still, as a sinister spectre. Immediate shock and dull anguish: what's going on? We don't understand, we're unable to name the difficulty, to pinpoint the problem. On all sides, there are threats, retreats, setbacks, bad news, aggravating twists and turns: nothing is working, everything is deteriorating... One question soon seems to sum up the feelings of those on the front line: ‘What's next?’” (Lagadec, 1994)

To face the times when emergency managers, need new knowledge to face unexpected events, LLMs can fill the voids of the knowledge base, and thus improve its emergency decision support, with an augmented ability to perceive and plan. Therefore, the augmented R-IO SUITE do not seek accuracy or technical scalability.

Knowledge generated by the LLM must be manually validated by emergency managers using R-IO SUITE before being added to the knowledge base. Therefore, if any information contradicts the existing knowledge base, the emergency manager decides which information to rely on.

4.2. Crisis use-case scenario

The scenario on which the experiment was based is as follows: R-IO SUITE is used to supervise a scientific research facility comprising several buildings, one of which contains critical, high-value equipment coveted by a malefactor. The experimental scenario takes place in three stages:

1. **Diversion:** the perpetrator cuts a gas line to trigger an alarm and lure the guards away from the equipment.

2. **Intrusion:** the intruder enters the building, triggers the intrusion sensors, and grabs the desired equipment, before escaping the way he came.
3. **Extraction:** the intruder cuts a gas pipe from another building before fleeing in a different direction, again to cause confusion and overload the alarm system.

The following Figure 9 shows the geographical location of the scenario.

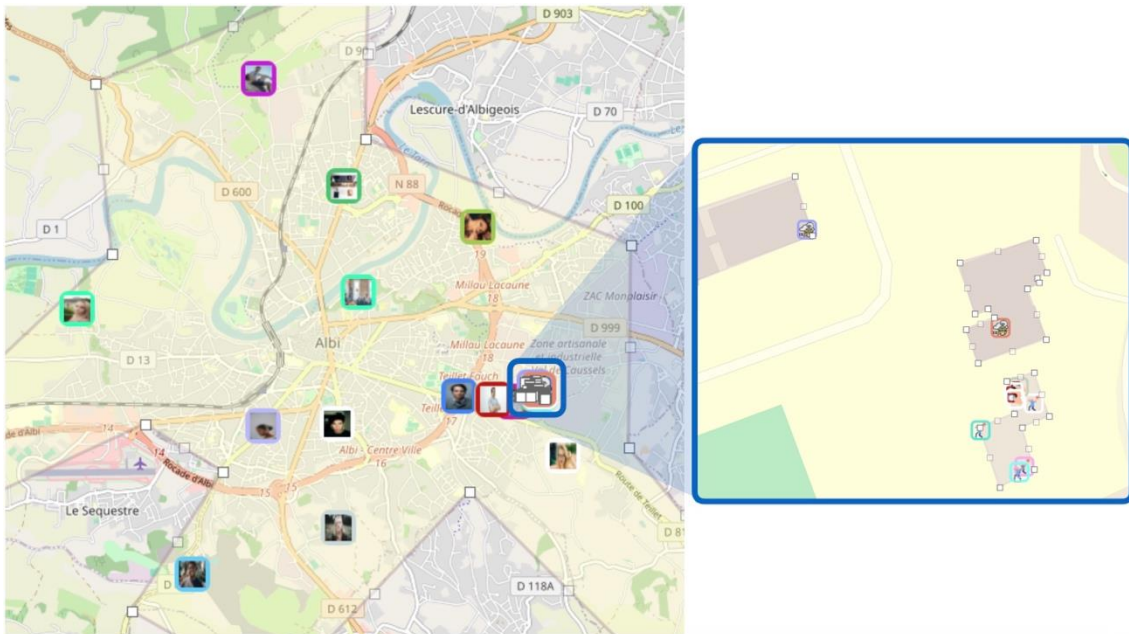


Figure 9. The general geographical situation of the crisis scenario.

The left side of Figure 9 shows the city in which the scenario takes place, as well as the location of certain actors identified and geolocated using the R-IO4U application (these may be janitors, on-call personnel, etc.). The right-hand part of the figure focuses specifically on the three buildings concerned, the gas sensors (purple and orange), the intrusion sensors (green, turquoise, pink, khaki, and white), and the equipment pull-out sensors (white). All the sensors are *dedicated sensors* (see Section 3.3.2).

4.3. Using this scenario to demonstrate the benefits of LLM for R-IO SUITE

4.3.1. Adding a new actor

If an electrician is present on site, but not on the knowledge base, the ‘inventRole’ function can be used, through the R-IODA application (see Section 3.3.1). Figure 10 illustrates the use of the actor creation interface of R-IODA (upper part of the figure), and the result provided by **ChatGPT©** integrated into the knowledge base used by R-IO SUITE in processing this scenario (bottom part of the figure). It can be seen that the electrician, and its skills, have been added as a *frozen* knowledge element (i.e. not yet an element of the situation model).

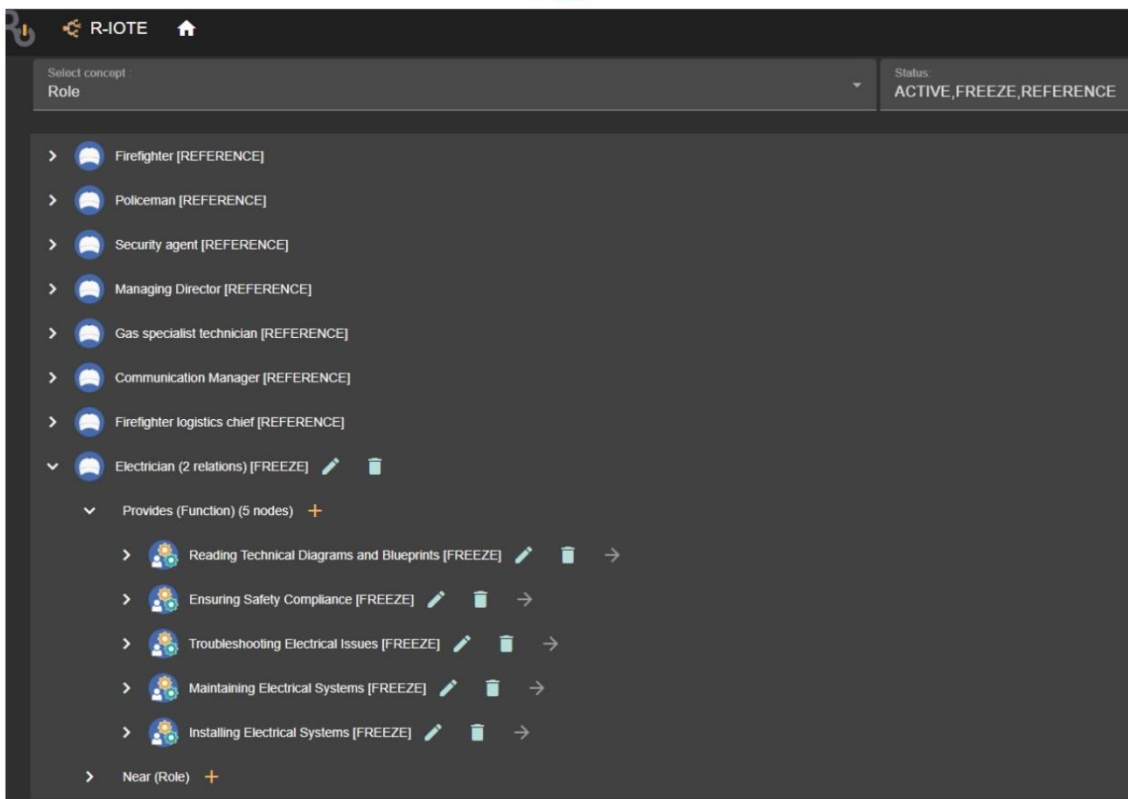
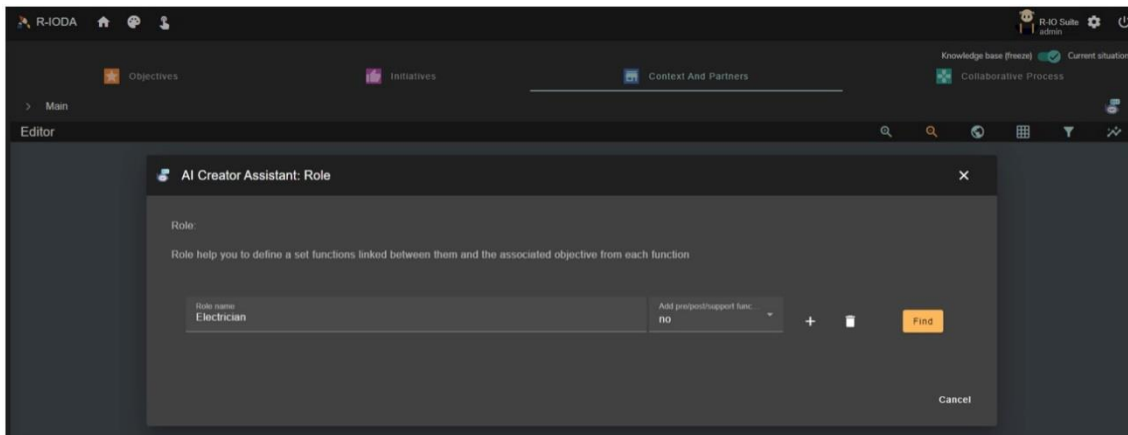


Figure 10. Adding a new role and the associated skills within the specific knowledge base of a use case.

4.3.2. Identifying a new risk

As soon as the intruder cuts the first gas pipe, gas is released and the gas sensor’s output goes from 0 to 1. The associated CEP rule is triggered and automatically adds a risk of explosion, a risk of fire, etc. All associated with predefined risks of the knowledge base (see Section 3.3.2). Emergency managers can then ask R-IO SUITE for a *response*

scheme. These elements are illustrated in Figure 11.

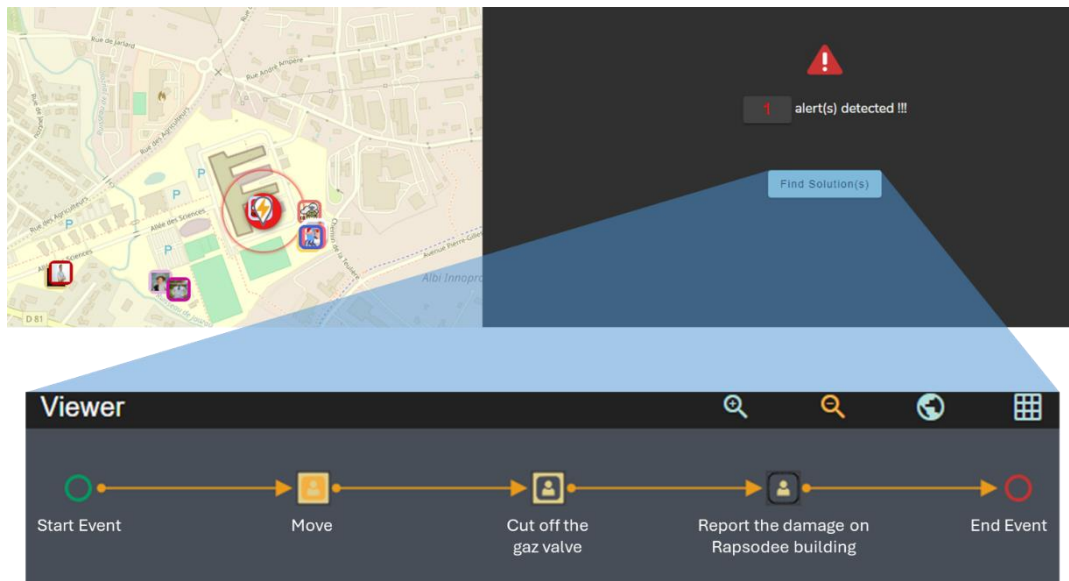


Figure 11. R-IO SUITE main interface and process deduction.

The upper left part of Figure 11 shows a cartographic view of the situation, where activation of the gas sensor threshold is visible as a red pulse. The upper right-hand part indicates an alert and the option to search for a solution, enabling R-IO SUITE to propose a *response scheme* in the form of a process model (lower part of the figure). In fact, by automatically consulting the knowledge base, R-IO SUITE can propose an on-site intervention task for a guard to intervene in the gas leak, framed by its pre-requisite (move to site) and post-requisite (writing an incident report) tasks. It is important to point out that there is no use of **ChatGPT©** at this stage because (i) the *actors* present are known and have been identified upstream, (ii) the *risks* and *facts* are also recognized from the data (gas sensor signal), and (iii) the response to the identified *risks* and *facts* is accessible from the knowledge base.

The deduced *response scheme* is then implemented (reaching the *Action* layer of Figure 3): A security agent is assigned the tasks, and therefore receives a notification on his R-IO4U mobile application, asking him to travel to the site. As soon as he arrives on site, he confirms completion of his task and receives his next task: cut off the gas supply

(left-hand part of Figure 12). He then realizes that the gas supply has been severely damaged. He cannot perform his task. He transmits a photo that is instantaneously analyzed as a new fact by ChatGPT© and thus added as a new objective on the situation map (center and right-hand parts of Figure 12).

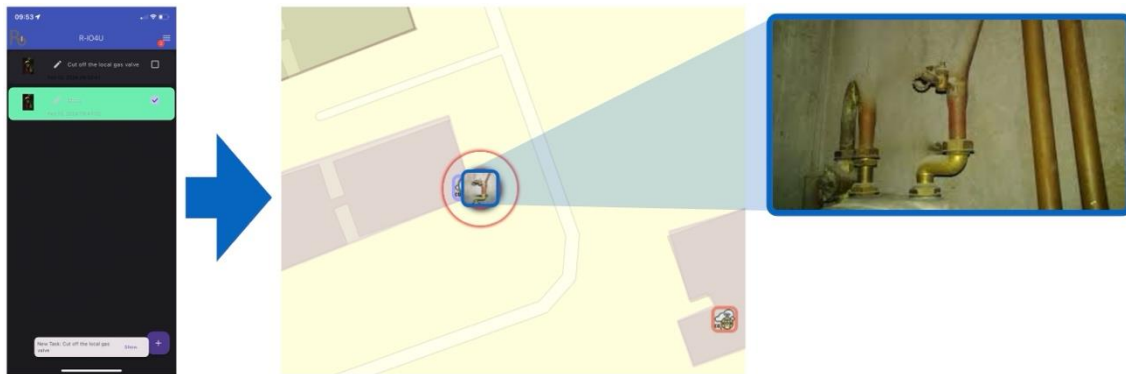


Figure 12. Photos to enhance the operational image of the crisis.

This addition triggers an anomaly. In the same time, an intruder enters the building. The intrusion sensor goes from 0 to 1. The CEP rules adds a new *fact*. R-IO SUITE automatically detects a divergence and alerts its users via R-IOTA (*Tracking Assistant*) (left-hand side of Figure 13). The emergency managers launches the deduction of a new *response scheme* (right-hand side of Figure 13): the unachieved tasks are interrupted (see red strikethrough tasks on the bottom right-hand side of Figure 13), while the ones already done are listed for information (see green tasks of Figure 13).

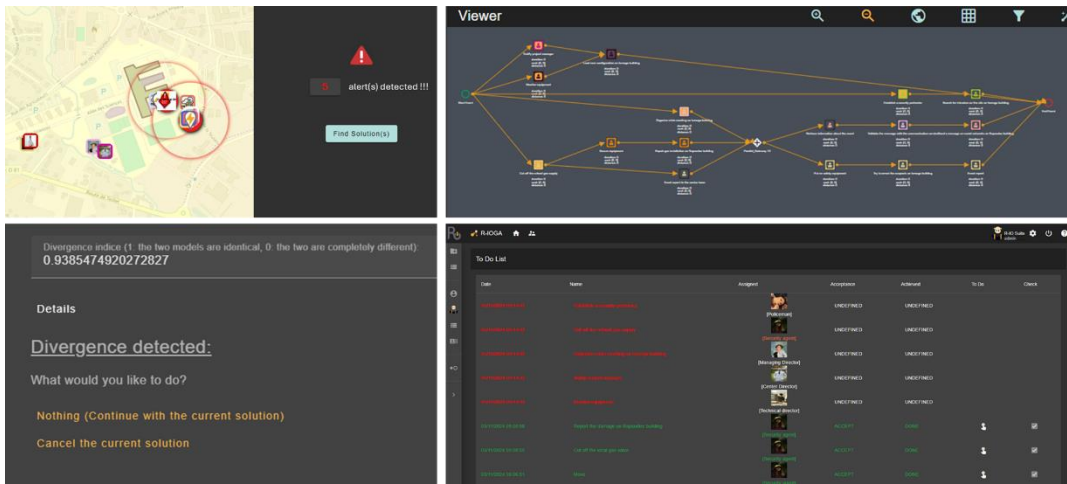


Figure 13. Adaptation of the response process based on new information interpreted by ChatGPT

4.3.3. Dealing with a newly uncovered objective

If the gas leak cannot be stopped by the security guard sent on-site, the gas leak may become serious. Thanks to the interaction with ChatGPT, the objectives associated with the gas leak are already known (see main panel of Figure 14, as explained in Section 4.3.2). If no solution is found (see the intermediate “Solution Deduction Report” panel in Figure 14), R-IO SUITE suggests a search, via ChatGPT, to suggest suitable roles and actors for these missions (see the final “Incomplete Process Detail Report” panel in Figure 14).

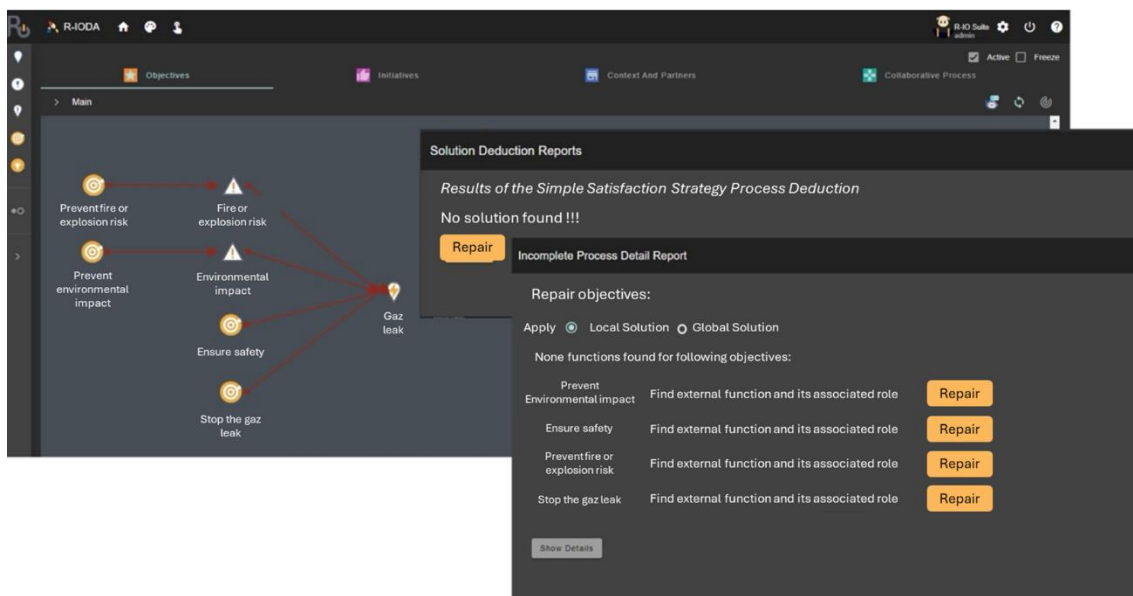


Figure 14. Analysis of uncovered objectives.

The emergency managers choose to interact with **ChatGPT©**. A search is launched, via the *'inventRole'* function (see section 3.4). In response, **ChatGPT©** proposes a "Safety Engineer" role covering all the objectives (see top of Figure 15). For illustration purposes, this role is assigned to a fictitious actor (left-hand side of the lower part of Figure 15), which then enables us to build the process associated with satisfying the orphan objectives (right-hand side of the lower part of Figure 15).

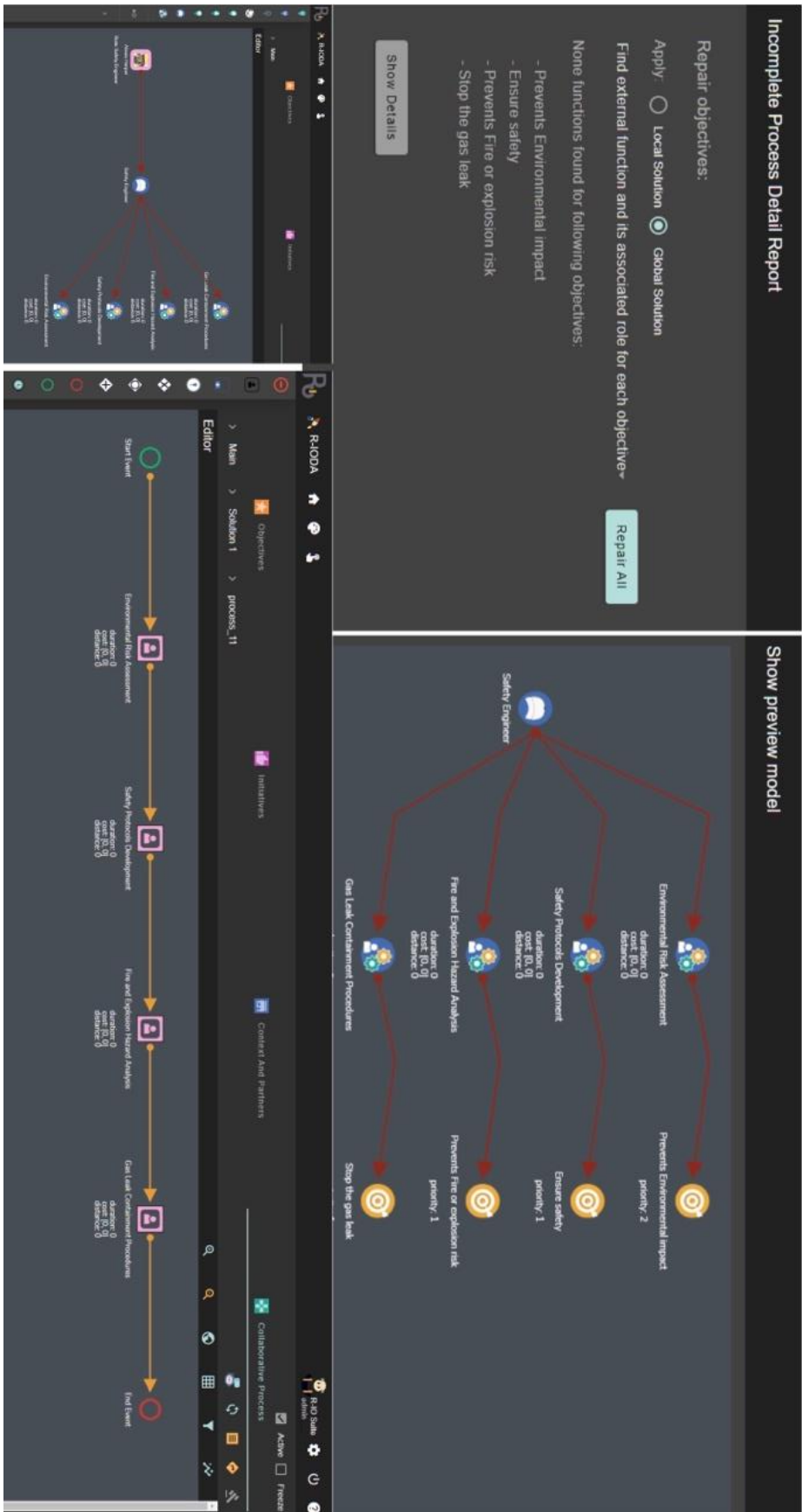


Figure 15. Adding a new actor able to deal with uncovered objectives.

4.4. Discussion

On a realistic case study, R-IO SUITE augmented with ChatGPT© enables to:

- An improved *comprehension level* ('ability to perceive'), by identifying unknown actors, their roles and functions (Section 4.3.1), or identifying risks and facts that may generate objectives to be addressed (Section 4.3.2). It uses both complex event processing and LLMs to respectively assimilate structured data streams and unstructured data. It replaces its machine learning models with an only LLM saving time and labeled data for training.
- An improved *exploitation level* ('ability to plan'), by suggesting roles or competencies that could be added to the response team to take on objectives associated with the crisis situation encountered that all the partners present are not currently in a position to address (Section 4.3.3).

Comparing R-IO SUITE augmented with ChatGPT© with the tools from the literature review, with the criteria applied during the literature review presented in Section 2, we can say that R-IO SUITE is the only one to use LLMs. It is therefore better able to adapt to the unexpected evolutions of a crisis, while being able to adapt to any kind of crisis, geographical context, or cascading effect, without further training.

5. Discussion and further perspectives

Model-driven platforms are powerful for knowledge management but often suffer from their coverage, completeness and maintenance. LLMs, on the other hand, offer a dynamic and comprehensive access to knowledge but lack explainable reasoning mechanisms. As proposed by (Benaben et al., 2020; Bénaben et al., 2016), this pushes for the use of complementary AIs. Combining these approaches can enhance the maturity of both artificial intelligence reasoning and knowledge management. LLMs offer the advantage of continuous evolution and quasi-universal expertise. Schematically,

platforms based on MDE approaches are generally powerful but ignorant, while LLM-based AIs are generally savvy but lacking in explainable reasoning mechanisms. **If big data has brought the statistical AI of the 80s back to the fore, what this article aims to demonstrate is that this statistical AI is likely to bring model engineering and knowledge management approaches back to the fore too.** The combination of the two will bring artificial intelligence as a whole to a higher level of maturity in terms of reasoning and explicability.

Another aspect of the discussion may concern the management by an MDE platform of the knowledge offered by the alliance with **ChatGPT©**. As presented in this article, this additional knowledge, whatever its nature, is not stored in its own knowledge base, but is used on the fly (in addition to the reference knowledge base, which is stored). This choice is based on the following arguments:

- Storing an ever-growing knowledge base would quickly become problematic on many levels (hardware, energy consumption, practicality, etc.).
- The knowledge base must remain reliable by avoiding either the uncontrolled storage of potentially questionable information or the need for massive human verification of stored information.
- LLMs can be considered as "synthetic experts" with quasi-universal knowledge. We can benefit from their constant evolution, which also makes them powerful but harder to maintain once integrated.

Finally, these LLM-based AIs have exactly this vocation: to be able to statistically answer any knowledge-related question. Let's recognize this ability and use them to accompany other AIs (e.g. MDE-based symbolic AIs) that are capable of reasoning logically and formally about this knowledge that they otherwise lack. These ideas have been developed in (Benaben et al., 2020; Bénaben et al., 2016).

In terms of perspective, there is also the possibility of using these AIs on closed (and reliable) document bases to enable them to provide something other than the instantiation of concepts, such as the construction of doctrinal rules, for example (from documents describing doctrines, best practices, feedback and regulations). This raises the level of intervention of these AIs (from being purely dedicated to "information generation" to one where the generated knowledge is intended for "information manipulation"). We might then consider positioning the interaction presented in this article at the level of "knowledge," while the perspectives evoked in this paragraph could correspond to a level of "knowledge about knowledge". Another perspective concerns the context-dependent use of LLMs to propose new functions, goals or actors compatible with what's already in the knowledge base.

This integration raises concerns about dependency, ethics, and trust. The European ethics guideline for trustworthy AI underlines the fact that *'AI systems should empower human beings, allowing them to make informed decisions and fostering their fundamental rights.'*(European High-Level Expert Group on AI, 2019). The role of AIs like **ChatGPT©** requires careful human validation to avoid errors and bias, and the existence of this validation step doesn't necessarily imply that the human in charge of carrying it out does so with conviction and seriousness. The door is therefore open to technical or human short-circuiting of this validation. From an ethical point of view, the dependence generated, and the associated risks (of error or approximation) clearly call for further reflection before considering the prospect of industrialization and societal use. In addition, if not trained internally, trained language models will never be fully accessible to users, as well as never be fully tailored to user needs. Besides, using external LLMs may pose risks related to data security and compliance, while real-time processing demands could lead to latency issues. A potential approach, following the methodology

of this article, is to combine internally trained language models specific to 'strategic' tasks (as discussed in (L. Wang et al., 2023)) with private large language models as a complement for tasks that cannot be handled with "in-house" tools.

Another consideration that emerges from this work concerns the question of the "death" of ontologies as static or even dynamic knowledge bases, since these AIs provide this knowledge in real time. Is there still any point in building such knowledge bases? Will ontologies be among the victims of the technological tidal wave generated by the invasion of these AIs? These scientific subjects need to bounce back and reinvent themselves, so that their contributions, approaches and vision are not diluted by the power of LLM-based AIs.

To conclude, we may venture to state that the implicit pattern that emerges from this article concerns more generally the ability of conversational AIs to instantiate abstract concepts and thus enable the translation of their knowledge into any structural pattern (metamodel). In our view, the proposed proof of concept is extremely powerful and opens the door to uses which, by combining these two approaches, bridge the gaps between model-based AI and LLM-based AI, thus opening the door to an infinitely promising unified AI. The richness of this perspective must, however, put into perspective, on the one hand, the inordinate benefits glimpsed and, on the other, the ethical constraints engendered.

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