Knowledge on demand: the future of decision support systems?

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ABSTRACT

The availability and quality of the information system supporting crisis management depends on the existence of up-to-date, comprehensive and reliable knowledge bases, despite the multidisciplinary nature of the information to be exchanged, the actions, and the decisions to be taken. This article proposes a method to benefit from pre-trained language models to automatically update these knowledge bases at both design time and run time. We offer a model-based extraction process and a dedicated automated validation process. These two contributions are illustrated and discussed around a case study: an emergency decision support system used to prepare for and respond to an unexpected mass gathering at an abandoned French aerial base.

Keywords

Decision Support System, Knowledge Base, Generative AI, Crisis Management, Information Management

INTRODUCTION

Disaster management is usually structured around four phases: prevention, preparedness, response, and recovery (Alexander, 2002; Altay & Green, 2006). During a crisis response, situational awareness is the key to efficient and effective management of the situation (Coche et al., 2021; Endsley, 2001). Decision-making processes rely on a good understanding of the situation. In the context of the ever-growing amount of available data coming from the crisis sites, crisis responders can rely on decision-support systems that are able to process it through previously acquired knowledge. These systems are very useful in offering visualization and analysis tools to increase the understanding of the situation, but to function, they rely on a knowledge base. This knowledge base needs to be filled before the crisis and updated every time the situation evolves. This is crucial to ensure that the model of the situation given to the crisis responders is always relevant and represents what is currently going on. If extracting information about crises during the preparation phase has become rather easy, the question is how can they (i) fit into the structure of the knowledge base and (ii) be integrated with pre-existing knowledge to feed the situation model and eventually result in relevant and efficient decisions. How can the knowledge base of decision-support systems be filled with information and knowledge, both before and during the crisis? There are several ways to fill a knowledge base with information before the crisis, but the urgency and unexpectedness of crises make it impossible to have fully and sufficiently complete knowledge bases. This means that a way to update and complete the knowledge base during the crisis, to keep up with the ever-changing situation, has to be found.

The task of knowledge base population then consists of finding, for the situation under configuration, all instances of metamodels concepts as well as the relations that link them. As the crisis evolves, both instances and relations can be modified or updated. Some new instances may appear (a new risk is arising), and existing instances may see their relations with other instances appear or evolve (a resource is no longer available in a given area, the arisen risk impacts one or several actors). This constantly evolving nature of crisis associated with the high amount of information to be integrated to render a relevant model of the situation justifies the need to automate the updating of previously evoked concepts. This leads to the problematic addressed in this paper: How can we keep knowledge bases up to date without overwhelming managers in nominal mode, before the crisis, and in emergency mode, during the crisis?

Section 2 presents the context of the study and feedback on the use of conversational AI to update an existing knowledge base at design time and run time. Section 3 presents a literature review of the existing solutions to automatically fill knowledge bases. Section 4 presents our proposal to keep our knowledge base up to date without overloading emergency managers. Finally, Section 5 concludes with the impact and benefits of our feedback and proposal.

CONTEXT: THE DECISION-SUPPORT SYSTEM R-IOSUITE

This section presents our feedback on the use of pre-trained language models to facilitate the instantiation of the knowledge base of a decision support system: R-IOSUITE. R-IOSUITE is an open-source software dedicated to emergency management Salatgé and Rebière-Pouyade, 2023.

R-IOSUITE Before Conversational-AI

The decision-support system (DSS) R-IOSuite presented in Fertier et al., 2020b aims to help decision-makers and crisis responders solve the crisis most efficiently. It has four main functionalities to achieve that goal: (i) manually populate a knowledge base and model a crisis situation (ii) automatically interpret data flows, real or simulated, to update their model according to the current situation (Interpretation functionality); (iii) deduce, orchestrate and supervise a process combining human or automatic tasks to react to the current situation (Deduction functionality); (iv) adaptation to adverse events (Adaptation functionality). All these functionalities depend on a knowledge base, where R-IOSuite stores and infers information. The information concerns both general, core, knowledge common to several crisis instances, as specific, application, knowledge describing one particular site (location, sensitive building or infrastructure nearby, geographical information...) and its available stakeholders (firefighters, policemen, trucks or ambulances...). It is structured by a meta-model dedicated to represent collaborative situations (Benaben et al., 2020): the objectives, actors, resources, or risks, and their undergoing relations.

There are several ways to fill the R-IOSUITE knowledge base: manually with experts in design time (approximately 80% of the knowledge), during the preparation phase, manually in run time by the emergency managers during the response phase (1%), automatically in run time during the response phase (Coche et al., 2021; Fertier et al., 2020a) via machine learning (text from tweets, images form tweets) or complex event processing (sensor data and open data) (19%).

To illustrate the manual and automatic update of a knowledge base in R-IOSUITE, we propose a case study on an unauthorized mass gathering in a decommissioned airbase, developed in the context of the PICADORS research project. This project is funded by the European Union through the Région Haut-de-France. The unauthorized aspect of this use case enhances the unexpected side of crises and the need to find ways to fill the knowledge base during the crisis, as the situation changes. Several actors are involved in the resolution of this crisis: the firefighters, the police, the French Red Cross, and the Prefecture of Cambrais where the aerial base is located. These actors have skills and competencies that must also be stored in the knowledge base so that the DSS can use that information to attribute the process' tasks.

R-IOSUITE Using Conversational AI to Fill Its Knowledge Base

Another possibility to fill the knowledge base would be to directly use conversational AI. This possibility can be used before the crisis, in the preparation phase when the knowledge base is filled with the available resources and concepts, but also during the crisis if the situation evolves and must be updated quickly. This second option is particularly interesting because it allows to enrich the knowledge base quickly, without having to look for information in operation plans or documents which can sometimes be hard to find. In the following subsection, we describe these two possible uses.

Filling the knowledge base before the crisis

Many of the actors involved in crisis management are the same from one crisis to another. This means that it is possible to anticipate the crisis by filling the knowledge base with information that is relevant in any kind of situation: for instance, a firefighter can extinguish a fire, and that is always true. To fill the knowledge base with this kind of information, it can be done manually, by automatic information extraction such as presented in the previous section, or with conversational AI.

In R-IOSuite, the knowledge base is filled with concepts such as roles that have functions: the role ”firefighter” has functions such as ”extinguish a fire” or ”rescue people”. It is possible to define these roles and functions either manually, or by requesting a conversational AI such as Chat GPT or Google Bard. In this case, the AI responds with several propositions that must be validated by the users of the DSS.

In the PICADORS use case, we asked the AI to help us find the functions of the actors from the Red Cross. It resulted in a list of possible functions such as treating injuries or sorting casualties. Among this list of functions, we were able to choose the ones that we thought were relevant to the use case and store them in the knowledge base.

Filling the knowledge base during the crisis

One of the characteristics of a crisis is its unexpected aspect. It is impossible to foresee every possible evolution of the situation and to be prepared for every possibility. Thus, it is necessary to be able to quickly modify or complete the knowledge base to keep it up-to-date. There again, it can be done manually, or with information extractions, but in some cases, it might be useful to use conversational AI.

In the PICADORS use case, we can imagine that the evolution of the situation requires at some point that some new actors get involved. If this evolution is unforeseen, the functions and skills of these new actors are probably missing from the knowledge base, which means that the DSS is unable to involve them in its response process proposal. Thus, we need to complete the knowledge base before asking R-IOSuite to deduce a new response process relevant to the new situation. Thanks to conversational AI, it is possible to quickly find the functions corresponding to the new actors and integrate them into the knowledge base if they are judged relevant by the decision-makers.

Benefits and Limits of Conversational AI to Fill an Existing Knowledge Base

The use of conversational AI-enabled us to reduce the time needed to implement the use case in R-IOSUITE. It also enables us to complete a knowledge base to cope with unexpected events, requiring specific knowledge that we wouldn't have thought of at the design stage. However, superfluous knowledge is added (noise) in the same way as missing knowledge, and AI cannot ensure the authenticity of the knowledge generated.

LITERATURE REVIEW ON DIFFERENT METHODS TO FILL THE KNOWLEDGE BASE

The aim of this section is to determine the extent to which a pre-trained linguistic model or machine learning models can be used to automate the updating of an information system's knowledge base, at both design and runtime.

Knowledge is available across an extensive collection of sources, ranging from structured data (databases, graphs, spreadsheets, etc.) to semi-structured (markup and JSON documents) and unstructured data (texts, such as PDF files, website pages, social media posts and comments, etc.).

Understanding, tagging, and structuring this large amount of data available from the web space into knowledge bases cannot be entirely achieved by hand, especially in the time-sensitive context of crisis management. Moreover, it is necessary to align the collected data with the existing knowledge structure on which the decision support systems rely (namely ontologies in the broad sense – as Gruber, 1993 originally defined it –, from OWL ontologies to knowledge graphs). The knowledge base population steps must then be automated to lessen the human effort and speed up the process of non-added-value tasks.

The literature review is based on the Scopus database, from 1980 to 2024, on the title, the abstract, and the author keywords fields. Table 1 presents the four parts of the query linked with the AND operator. It searches for publications about automated techniques of knowledge extraction, acquisition, population, feeding or collection of structured knowledge.

The first part of the query [1] looks for tools for structuring data in the broad sense (hence the use of keywords such as ontology, structure, base, etc.). The second part [2] seeks ways to get this knowledge automatically. The third part [3] focuses on the crisis management application domain. The fourth and last part of the Scopus query filters results by excluding domain areas that are not relevant to the research question (e.g., ”VETE” for veterinary and ”DENT” for dentistry).

The 56 papers returned by the query are filtered regarding their relevance with crisis domain and knowledge extraction concern. The 10 remaining related works are presented in Table 2 and evaluated through three criteria which are (1) the automated nature of the proposed extraction method, (2) the ability to refer to existing knowledge structure, (3) the complexity of extracted relations and (4) the type of processed data. The first column indicates the article reference. Columns 2 to 4 present our three criteria. Column 5 indicates which kind of data was used to perform knowledge extraction.

Table 1. The Scopus query

Operator	Number	Part of the query
	[1]	(base* OR database* OR structure* OR repositor* OR model* OR ontolog*) W/1 (knowledg* OR data OR fact* OR relation* OR entit* OR ontolog*)
AND	[2]	automat* W/1 (extract* OR acqui* OR populat* OR feed* OR collect*)
AND	[3]	cris* OR disast* OR ”adverse event*” OR ”unexpect* event*”
AND	[4]	EXCLUDE (SUBJAREA , ”DENT”) OR EXCLUDE (SUBJAREA , ”VETE”) OR EXCLUDE (SUBJAREA , ”NURS”) OR EXCLUDE (SUBJAREA , ”CENG”) OR EXCLUDE (SUBJAREA , ”IMMU”) OR EXCLUDE (SUBJAREA , ”PHAR”) OR EXCLUDE (SUBJAREA , ”CHEM”) OR EXCLUDE (SUBJAREA , ”MATE”) OR EXCLUDE (SUBJAREA , ”ARTS”) OR EXCLUDE (SUBJAREA , ”PHYS”) OR EXCLUDE (SUBJAREA , ”EART”) OR EXCLUDE (SUBJAREA , ”BIOC”) OR EXCLUDE (SUBJAREA , ”MEDI”)

Table 2. The results of the literature review organised according to our four criteria. ***Abbreviations : N.R Not Relevant; N/A Not available***

Reference	Automated method	Compliance	Complexity	Data
Angeles and Kijewski-Correa, 2022	No	Yes	Model specific	images, texts
Bayramoğlu and Uzar, 2023	No	Yes	Taxonomic	images
Chasseray et al., 2021	Yes	Yes	Taxonomic	texts
Chaulagain et al., 2019	Yes	No	Taxonomic	texts
D'Amico et al., 2011	No	Specific	Non taxonomic	discussions
Guo et al., 2023	No	No	*N.R.*	images
Nguyen et al., 2011, 2012, 2013	Semi	Yes	Non taxonomic	tweets (semi-structured)
Venkatachalam et al., 2020	*N/A*	Yes	*N/A*	texts
Wang et al., 2020	Yes	Specific	Non taxonomic	texts
Zong et al., 2022	Semi	BDD	Non taxonomic	tweets (semi-structured)

A few related works extract territorial information that are relevant in case of a crisis based on aerial data. Bayramoğlu and Uzar, 2023 focus on the inventory of roads from unmanned aerial vehicle images. Similarly, Guo et al., 2023 identify cropping zones that have been affected by bad weather conditions and are susceptible to crop lodging. They use satellite image and image processing techniques to identify the concerned zones. In the same area of research, Park et al., 2015 build topographic landscape representation, and notably tree height for the management of disasters such as forest fires. As techniques presented in these articles are relevant in term of information extraction, they do not involve the population of an existing knowledge structure or are not related to a decision support system. Bayramoğlu and Uzar, 2023 is the only one proposing an ontology built on 4 classes to reference extracted elements such as Bicycle (road), Sidewalk, Road and Marking. However, these classes are not pre-existing the extraction method and are designed on purpose based on the extraction task results.

Angeles and Kijewski-Correa, 2022 couple image sourced information extraction with semi-structured textual data such as tax assessor data or building permits. Their framework results in a model characterizing the sensibility of buildings. This model can be reused in case of a crisis or disaster inducing high winds. However, as no pre-existing knowledge structure is used, the created models can't be easily integrated in a more global crisis management system.

More generally, Babič et al., 2022 list a wide group of ontology learning tools that can be used in the case of crisis management for the building of a knowledge structure. These tools are nevertheless not relevant when dealing with an existing knowledge structure such as a metamodel or an ontology which has to be populated and not rebuilt from scratch.

Nguyen et al., 2011, 2012, 2013 propose the definition of earthquake semantics networks, that can be populated from tweet analysis and further integrated in a crisis management system. As such a knowledge management system ensures interoperability with crisis management systems, the population of the expected knowledge graph from tweets requires prior training steps and associated training datasets which makes the approach not fully automated.

Some automated extraction methods for crisis have been proposed in the literature. Chaulagain et al., 2019 use named entity recognition and the definition of specific patterns for the extraction of crisis-related components (number of deaths, injuries, date and locations). Similarly, Chasseray et al., 2021 apply their domain-independent ontology population patterns to a crisis metamodel, for the extraction. As the proposed methods in these works are both automated, they focus only on taxonomic relations (extraction of concept-instance relations) and do not tackle the domain-specific relations that may occur between two instances of a knowledge base. **Is there a possibility to benefit from pre-trained linguistic models, while limiting the generation of noise and optimizing the authenticity of the generated knowledge?**

PROPOSAL

As natural language processing can be used to populate a knowledge base, their performances are highly dependent on the domain and considered case study. This section discusses the possibility of designing extraction systems encompassing a larger amount of information. As enlarging the volume of extracted information also supposes a rise in irrelevant information, a proposition is made to pair the extraction systems with a conversational AI that could be used as an automated validation tool in order to filter the generated noise.

Natural Language Processing for Relation Extraction

Considering the fact that exploited data is of a textual nature, the field of Natural Language Processing provides a large pallet of tools that can be mobilized to extract knowledge based on unstructured data. Among all tasks of natural language processing, two are relevant for knowledge base population which are instance extraction and relation extraction.

Instance extraction identifies in textual data, pieces of text that can semantically be linked to an existing concept as an instanced version of this concept. This is especially used in ontology and knowledge graph population, as it allows, from a set of defined concepts, to extend some of them with real-world instances.

Relation extraction is a process that aims at extracting semantic meaning linking to parts of a given text. Commonly, the parts to be linked through a relation correspond to instances of previously defined concepts (author-artwork, country-capital city, athlete-discipline).

Our illustrative case study focuses on the extraction of relations between role instances (Firefighter, Caregiver, Policeman, Military person, RedCross, Institution, Officials, Security agent) and function instances (Establish a perimeter on site, Extinguish a fire, Launch an alert, Heal a victim, Drive an engine). We state that instead of extracting instances and relations in separate processes, it is either possible to use the former to extract the latter or to extract both in the same process.

In our specific case, a scenario can be imagined where the objective is to know which Role is involved in the crisis and which Function this role has (what is a policeman able to do in case of a fire ?). This need exists both during the preparation phase and response phase, as associations between a Role and a Function may also appear during a crisis, due to its evolution, if a Role sees itself granted with new functions for example.

Knowing that RedCross is a role, and Protect people is a Function, the goal of the first approach is to identify all occurrences of the RedCross instance and Protect instance in a given text and see if they can be related in the text. This approach is relatively direct, but supposes that instances are already known.

When, none of these instances is identified however, another approach could be to drive the extraction with information contained by the semantic meaning of the relation linking the two concepts. Knowing the type of relation that we want to extract is a great advantage regarding the diversity of textual data. The proposed rule-based approach, presented in Figure 1, hence relies on the richness of verbal relation in textual data and the information they provide to identify instances. For each relation identified in the metamodel, the extraction process can be decomposed into three main steps:

1. Identifying all active verbal forms that may traduce the relation identified between the two concepts of interest. In the case of Role-Function relations, this list can contain verbal forms such as *Is able to*, *Can*, *has to*, *acts to*, *Is tasked with*, *Is capable of*, for example all traducing the ability of a Role to operate a task (Function).
2. Based on the identified forms, build all possible triples involving one of the verbal forms identified in the text and extract the pieces of text that the verbal form links using a predefined extraction pattern structure.
3. Validate the triples and register them in the knowledge base linking each piece of text to its attributed concept (attributed concepts are known as they are linked to the relation in the metamodel).

This approach is relevant as it does not need any pre-training on data specifically related to the crisis domain, as would a language model dedicated to crisis management area for example.

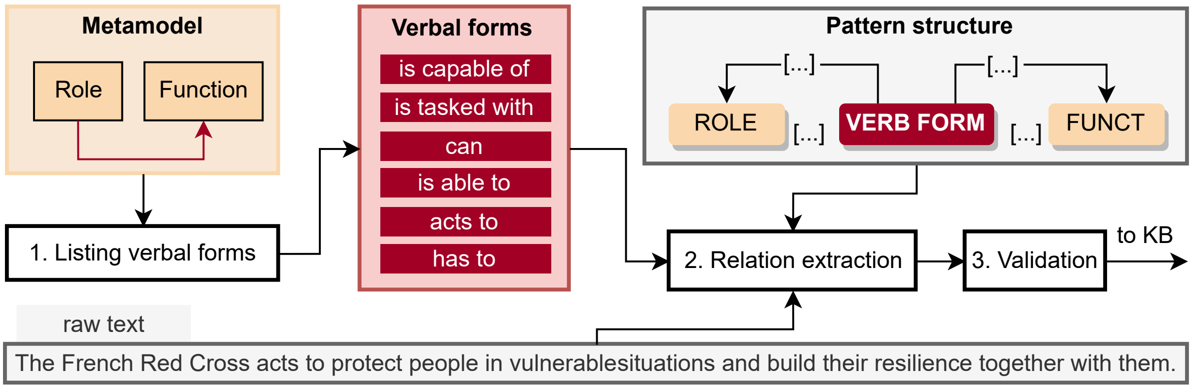

Figure 1. Proposed pattern-based extraction process of Role-Function relations

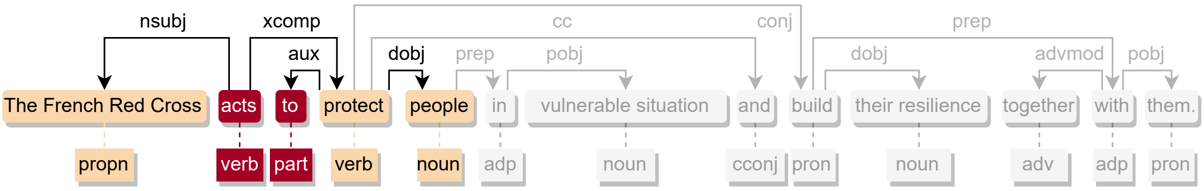

Figure 2. Application of a restrictive Role-Function extraction pattern

Defining Covering and Generic Extraction Pattern

Step 2 of the proposed approach can be performed through the application of extraction patterns. A main limitation of extraction patterns however is that even though they are very precise when specifically defined, they can miss a lot of information. If this information is expressed through a slightly different expression, a pattern that previously worked and extracted the wanted information is no longer effective. Loosen the pattern, at the opposite, tends to greatly extend the range of covered possibilities, but in counterpart, may lead to the extraction of a lot of irrelevant or false information.

Figure 2 and Figure 3 show two examples of extraction patterns being respectively restricted to direct expression of a function (figure 2) and extended to encompass more possibly valid relations 3. In the represented sentence : *The French Red Cross acts to protect people in vulnerable situations and build their resilience together with them.* Two Role-Function relations can be identified and should be extracted which are the relation between the Role *Red Cross* and the Function *Protect people* and between the Role *Red Cross* and the Function *build their resilience*.

To extract these relations, a possibility is the definition of extraction patterns, adapting the definition of patterns proposed by Chasseray et al., 2023, which allows the generic extraction of concept-instance relations so that they can extract relations based on previously defined verbal forms.

First pattern (2) looks for the restricted extraction of the following sequence of tokens:

$$\text{PROPN} \xrightarrow{\text{nsubj}} [\text{VERBAL FORM}] \xrightarrow{\text{xcomp}} \text{VERB} \xrightarrow{\text{dobj/pobj}} \text{NOUN}$$

Where :

1. the NOUN may later be defined as a Role,
2. the RELATION VERBAL FORM matches with one of the verbal form defined in step 1,
3. the VERB $\xrightarrow{\text{dobj/pobj}}$ NOUN sequence is used to identify a potential Function.

Using such a pattern on the example results in the extraction of one correct function in that context (*protect people*). This pattern can nevertheless be criticised as it misses the second function expressed in the sentence (*build their resilience*) as it is restricted to a limited group of expressed relations.

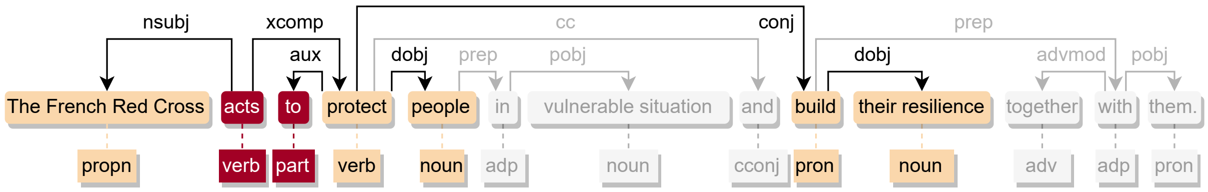

Figure 3. Application of a loose Role-Function extraction pattern

A larger extraction pattern looking for a more generic sequence of tokens:

$$\text{NOUN} \xrightarrow{\text{any}} \ldots \xrightarrow{\text{any}} [\text{VERBAL FORM}] \xrightarrow{\text{any}} \ldots \xrightarrow{\text{any}} \text{VERB} \xrightarrow{\text{dobj/pobj}} \text{NOUN}$$

allows the extraction of every candidate on each side of the matched VERBAL FORM, without paying attention either to the nature of syntactic dependencies linking the different elements to extract or the length of the dependency path linking them. In the provided example (see Figure 3), this pattern performs well as it is able to extract both targeted relations.

Contrarily to specific dependency patterns described in Chasseray et al., 2023, this extraction pattern is agnostic regarding the nature of the dependency links, which ensures a wider coverage and a larger amount of extracted information.

However, as relaxation of the extraction pattern can be seen as a solution to cover all needed information, the risk is flooding the relevant information in too much noise. When applied to larger textual content, a larger pattern might then include numerous relationships, some of which may not be semantically correct, leading to an accumulation of incorrect triples, that will surely extend the validation task. In that case, manual validation of extracted triples is not reasonable, especially during the response phase, where deduced scenarios and taken actions should be proposed as fast as possible to decision-makers.

Assisting Validation Filtering with Conversational AIs

In the methodology proposed, the third step is crucial to ensure that the knowledge base is provided with information that is correct, and sufficient for scenario deduction. This inherent nature of pattern extraction is in conflict with the objective of a complete model of the situation, by stating that too precise patterns will not extract all the available information, resulting in an incomplete model.

Despite the fact that conversational AI outputs are raising questions concerning their relevance or the lack of sources from which they suffer, they can be used as a tool to validate already extracted (and sourced) knowledge.

Directly asking a large language model and its associated conversational AI to populate a knowledge base remains questionable depending on scenarios and use cases for two main reasons which are (i) the impossibility of tracking the origin of the extracted information and (ii) the risk to face inferred knowledge and add apparently realistic information, that does not exist in real life, or not in the current situation.

However, using such conversational AI as a post-extraction validator does not affect the whole knowledge base population system as it is provided with traceable information, and only states its validity. We propose a first algorithm flowchart diagram in 4 to automate validation using conversational AIs. The proposed methodology lies on predetermined verbal forms and extracted relations to generate different prompts for validation. Generated prompts are submitted to a conversational AI and validation outputs (True/False statement + confidence) are aggregated to establish a general True/False statement on the relation. Extracted relations that are stated as False by the conversational AI are ignored. Validated relations are however added to the knowledge base. Human validation is however still required to confirm the extracted relation as true and available for further use by a decision support system. This is mandatory, as conversational AIs and Large Language Models can falsely qualify an extracted relation as True. Implementation of such a knowledge extraction framework can be parameterised with a threshold stating when a relation should be considered True or False. This threshold could be set on the average rate of decision, but can also use the confidence indicator.

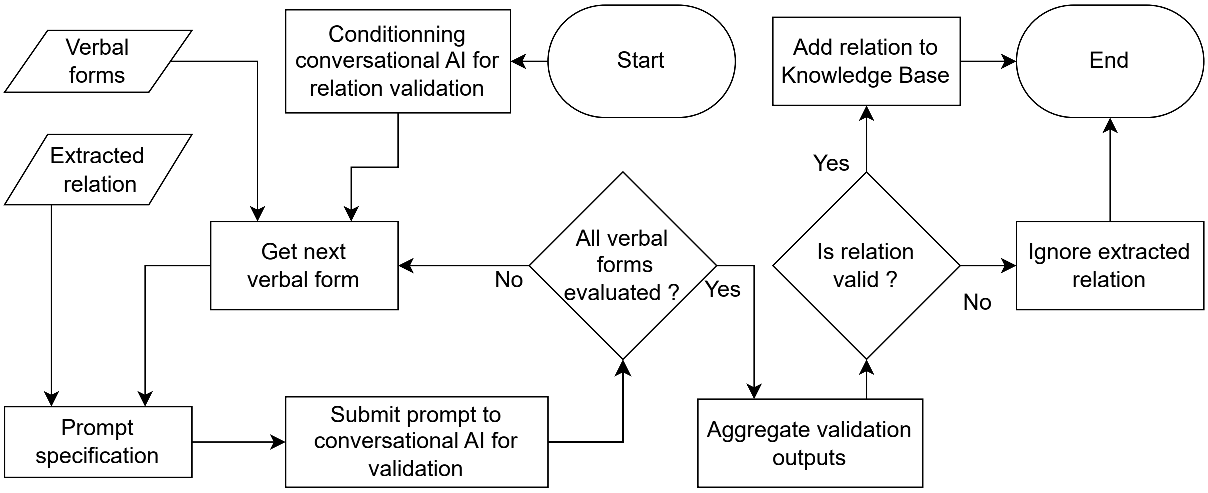

Figure 4. Flowchart diagram for the automated validation process of extracted relations

DISCUSSION ON IMPACT AND BENEFITS

The use of the methodology proposed could improve the ways to fill the R-IOSUITE knowledge base: automate part of the manual updates with experts in design time (at least 80% of the 80%), during the preparation phase; automate part of the unexpected manual updates during the response phase (at least 50% of the 1%); and improve the interpretation of texts or images from tweets, during the response phase; while limiting noise and optimizing the authenticity of the knowledge generated.

For the French fire department in the Pas-de-Calais department, our method of preparing and assisting a response to an unexpected mass gathering has enormous potential. This innovative approach could revolutionize crisis management by enabling pre-filling and automatic, controlled updating of the knowledge base of the emergency decision support system. What's more, in the event of a crisis, this system could prove invaluable in enabling the reconfiguration of prepared emergency plans. This would guarantee a more informed and effective response.

CONCLUSION

This paper presents four contributions: a feedback on the use of conversational AI to instantiate a knowledge base at design time and run-time; a literature review on existing systems able to automatically instantiate a knowledge base in the crisis management field; a method to extract instances and relations (patterns); and a method to automatically validate the extracted patterns.

The example provided in this article is detailed for illustration purposes. Future work on this subject could consist of systematic implementation of the proposed AI-assisted knowledge base population methods to apply it to several crisis cases and assess its adaptability to different use cases.

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