Towards a Case-Based Support for Responding Emergency Calls

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Abstract. In emergency situations, the quick and precise initiation of rescue measures is crucial. Dispatchers are responsible for answering emergency calls and deciding about measures and resources. However, currently there is no support on the basis of an intelligent system that is able to exploit experiences from previous situations. Therefore, we propose a concept for a case-based support for emergency call handling in this work. First, we investigate where case-based reasoning can be applied in the decision process and sketch our vision of a hybrid intelligent approach that combines expert and experiential knowledge. For the case-based approach, we focus on deriving adequate measures and resource types. Furthermore, we propose a mechanism that supports the dispatcher in the choice of the questions such that precise decisions can be derived. The approach is prototypically implemented and will be evaluated with experts in future work.

Keywords: Case-Based Reasoning · Knowledge Management · Hybrid Artificial Intelligence · Emergency Management .

1 Introduction

Public Safety Answering Points (PSAP) are the first point of contact for individuals in situations that pose a danger to life and limb seeking professional emergency assistance. PSAP operators are trained to handle emergency situations through gathering essential information from callers to initiate appropriate measures and dispatch the necessary resources efficiently. They have to make precise decisions under time pressure, as some diagnoses, e.g. stroke or heart attack, are life-threatening and every second reduces the chance of survival. In addition, the capacities regarding resources and personnel of the control centers are limited. The problem is further exacerbated by the ever-increasing volume of calls. In 2021, there were nearly 17 million calls in Germany to the emergency number “112”, which excludes issues addressing the police [1]. This includes a large number of calls that do not count as emergencies and therefore unnecessarily tie up capacity [13]. For these reasons, the optimal use of control center resources is a major challenge. Nowadays, the PSAP operators in Germany are currently supported by a very rigid and rudimentary system based on a decision tree that covers the most necessary aspects of emergency call inquiries, but lacking intelligent and flexible support.

The SPELL[3] project addresses decision support in the context of emergency management. To this end, a semantic platform is developed that integrates data from various sources and manifold services based on Artificial Intelligence (AI). One of those services is a rule-based approach towards an intelligent support for emergency call handling that exploits acquired medical and firefighting-related expert knowledge. To this end, rules are manually modeled on the basis of an ontology pursuing a data-driven approach [17,24]. Nevertheless in some cases, the ideal handling of emergency situations goes beyond this modeled knowledge, and experience is helpful. In order to systematically exploit the experience of the PSAP operators, this paper presents an approach that utilizes experiential knowledge to support decisions made during emergency call handling in order to increase performance. The result is a first step towards a hybrid AI approach that integrates rule- and case-based reasoning (CBR) for emergency call handling with a focus on the case-based approach.

In Sect. 2 relevant foundations, such as emergency management and preliminary work are explained. Section 3 presents the conducted expert interviews in order to derive requirements. The proposed concept is introduced in Sect. 4. and the paper concludes with a summary and suggestions for future work in Sect. 5.

2 Foundations

First, emergency management in general is introduced and the aspect of emergency call response and its state of the art is described in detail. The subsequent section outlines the semantic platform of SPELL and the existing rule-based support for emergency call handling. The section concludes with related work on the use of CBR in emergency management.

2.1 Emergency Management

Emergency management refers to the organization and coordination of resources and responsibilities for dealing with all aspects of emergencies and disasters, whether natural or human-made. It consists of four phases: preparedness, response, recovery, and mitigation [26]. Preparedness refers to all activities taken in advance, like training. Response concerns immediate reactions to the incident such as dispatching resources. In the recovery phase, the affected objects are restored after the concrete hazard has passed. Mitigation considers long-term measures to increase resilience in case of future incidents.

In this work, we focus on the response phase and on the partial aspect of medical emergency call handling. Furthermore, as emergency call handling is

[3] SPELL is the acronym for semantic platform for intelligent decision and operations support in control and situation centers.

different in each country, we focus on Germany, but due to the same core objective, a potential transfer of results to other countries is highly probable.

In Germany, the central emergency number "112" can be called when encountering medical or firefighting-related issues. These calls are forwarded to the nearest PSAP based on the location of the caller. Emergency call handling is a highly complex process consisting of several different tasks and decisions. Call-takers are responsible for assessing the situation in dialog with the caller. This process of interaction between caller and call-taker can be sketched as an iterative cycle [21] (see left side in Fig. 1). With the given information and expert knowledge of the call-taker, a mental picture is created. Through this, it is decided about how the situation is handled in terms of measures to be implemented and resources to be dispatched, like an ambulance.

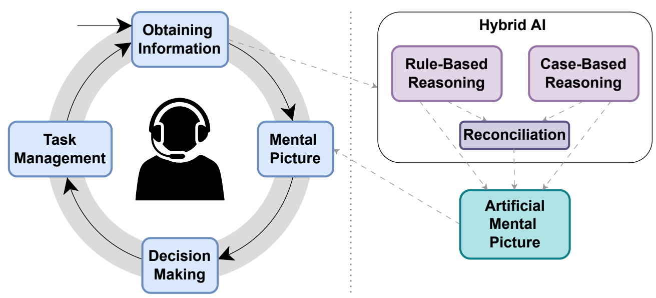

Fig. 1. Iterative Procedure of Emergency Call Handling by Call-Takers based on Møller et al. [21] (left) Extended with Hybrid AI based on [16] (right)

In some cases, depending on each emergency control center, the task of deciding for measures and resource types is assigned to the call-taker, whereas dispatching a specific resource is the responsibility of a dedicated dispatcher. For the sake of simplicity, we will not go into the separation of these two responsibilities any further, but instead use the term dispatcher for both.

This process of emergency call response is time-critical and the recommendation is that a maximum of 90 seconds elapse before resources are dispatched so that help arrives in good time in critical situations [11]. In addition, these decisions are usually made by a single person as it is a one-to-one connection between caller and dispatcher, such that they are based on personal medical knowledge and experience. This concerns several aspects [16]:

- deriving specific diagnoses or threats from paraphrases by a caller who has no specialist knowledge (e.g. chest pain as a sign of a heart attack)
- risk estimation through assessing the situation (e.g. surroundings of a fire)
- identifying the best measure to initialize and an adequate resource type (e.g. transport by an ambulance for a dialysis patient)
- choosing a specific available resource

Whereas in some countries, standardized emergency call handling systems are established, in Germany there is no such use due to a lack of acceptance of the dispatchers, as these standardizations are inflexible and induce a lack of scope of action [18]. In some PSAPs, structured emergency call responses are implemented through questionnaires that base on decision trees. These are specified by experts, but only cover certain sub-areas, such as particularly critical conditions. However, there is a strict order of questions to which the call-taker needs to adhere to or ask questions without support with the risk of forgetting important aspects and ultimately worsen the incident [17]. For this reason, there are situations, especially those that occur infrequently, where inexperienced dispatchers in particular are not optimally guided by the system and the integration of experiential knowledge seems promising and indispensable.

2.2 Intelligent Emergency Call Response

In the context of the SPELL project, first steps towards an intelligent emergency call handling have been done. The overall aim is to incorporate different kinds of knowledge, such as expert (e.g. rules) and experiential knowledge (e.g. cases). Thus, the iterative procedure of Møller et al. [21] is enhanced with hybrid AI methods that build up an artificial mental picture (see right side in Fig. 1). Here, new knowledge can be inferred by both AI methods, CBR and rule-based reasoning (RBR), and thereby support the dispatcher by suggesting decisions. For emergency call handling, we propose a hybrid AI approach that *co-processes* the information, which refers to a parallel application of RBR and CBR with the same objective [22]. Thus, both approaches could result in different decisions. To this end, a reconciliation step (see Fig. 1) might be necessary to decide for a best suggestion and not proposing contradicting results to the dispatcher. However, the reconciliation is not part of this work, but will be investigated in future research as essential part of the support for the dispatcher. Nevertheless, some decision might also be derived from only one AI method without using the hybrid approach but acting standalone.

The framework for this hybrid AI approach is given by Maletzki et al. [17] by proposing an Ontology- and Data-Driven Expert System (ODD-ES) for dispatchers with a focus on medical emergency calls. Here, the knowledge base is represented as semantically modeled functions for the integration of symbolic and subsymbolic AI. These functions are described through input and output which refer to individuals of an ontology concept. The functions itself range from simple logical functions to more complex AI-based services, like RBR or CBR.

In this work, we focus on the specific integration of RBR and CBR with a detailed concept for the case-based support for the regarded domain. The existing rule-based support is based on rules that are modelled in cooperation with medical experts. For instance, the three symptoms shortness of breath, cough and fever lead to a suspected diagnosis of pneumonia. As a rule, this can be expressed as follows: `IF shortness_of_breath AND cough AND fever THEN hint_pneumonia`, such that a hint for the diagnosis is given to the dispatcher. However, emergencies are highly individual such that the rules cannot cover everything. To this end, we propose a hybrid approach that combines implicit as well as explicit knowledge.

The foundation for such a hybrid AI approach is a common ontology that is used by both methods to enable communication. In the context of the SPELL project, a knowledge graph was build that semantically describes the emergency management domain. Thereby, emergency call handling with a special focus on medical knowledge was modelled in detail. This expert knowledge was acquired manually in cooperation with experts. The main concepts, derived from the tasks and decisions of the dispatcher, are illustrated in Fig. 2.

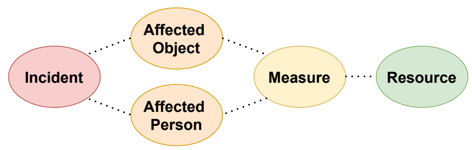

Fig. 2. Main Concepts of the SPELL Knowledge Graph - Abstract View

The overall knowledge graph contains all relevant information, in total more than 1000 concepts, that could come up during a call. Semantics contained in the graph, which can be exploited for similarity assessment, are several taxonomies, e.g. symptoms. Furthermore, publicly accessible context information like weather conditions or water levels is also represented in the knowledge graph. Since the SPELL platform serves as a central data pool through which data can be exchanged on the basis of the concepts of the knowledge graph, both approaches from the proposed hybrid AI approach can exploit the information obtained from the caller as well as context information by connecting to the platform.

2.3 Related Work

In preliminary work, we investigated how different AI-based methods can be used for decision support in emergency call handling [16]. In particular, we focused on hybrid intelligence, that refers to the combination of human and artificial intelligence. We identified exemplary integrations of AI methods in ODD-ES to support emergency call handlers, and outlined a mechanism for calculating reliabilities for conclusions based on experience in similar situations.

In the context of emergency management, several related approaches have been researched [6]. Most of them focus on larger incidents such as crises or environmental disasters, but not on smaller daily occurring emergencies [5,8,9,20,27,28] and rather regard organisational instead of operational aspects [4].

Althoff et al. [3] propose an approach for the support of medical decision tasks and focus on short response times and dealing with incomplete information, which are basic characteristics in the medical domain [3]. The authors introduce a novel data structure, named Inreca-Tree, for indexing large case bases. Attribute values are used to traverse the tree structure leading to diagnosis in the leaf nodes, similar to a decision tree. As rather few information is available in the emergency management domain, this data structure is not suitable, because in the worst case many symptoms would be assumed to be unknown, even if they are present leading to wrong results or otherwise if asking all attributes on the path in the tree, loosing valuable time until dispatching resources.

3 Analysis

Before designing a concept for a case-based decision support in emergency call handling, the process was analysed in detail for identifying the biggest potential for an improvement through an integration of experiential knowledge.

3.1 Interviews

In order to gain a deeper understanding of the possibilities of supporting the call handling and dispatching process with CBR, an explorative qualitative interview study was designed. We conducted four interviews with experts from the control center domain, two of whom are dispatchers. One participant is a medical director of the rescue service and responsible for quality management and developing guidelines for the dispatchers. The fourth participant is a specialist nurse for intensive care medicine, who additionally is studying in the management of health care services and in this context analyzed emergency calls. These experts have a minimum of ten years of professional experience. The semi-structured interviews were conducted using a designed interview guide, which consists of three topic blocks: information about emergency call handling in general, identifying current problems and potentials based on experiential knowledge, and presenting specific example scenarios where CBR could be useful.

Analyzing the results of the interviews, we find that there are significant challenges with a major impact on the effectiveness of decision-making. Of particular importance here is that decisions are largely based on the individual knowledge and experience of a single person. However, according to the respondents, a serious shortcoming is the lack of systemic support for decision making.

The most important aspect is the communication between caller and dispatcher. One of them uses a layman's language, while the other is responsible to translate it into expert terms. The information provided is unstructured and most of the times does not fit to the order of the questions in the existing questionnaire. Furthermore, in some cases the described symptoms do not fit into the specified schemes in the questionnaire, but are rather diffuse, rare or unknown disease patterns. In such cases the dispatcher tries to narrow down in order to find adequate measures and resources.

Another mentioned issue for emergency call response are so-called fixation errors, which describe the overly rapid commitment to a diagnosis or disposition decision and are a common problem for experts. Here, the next questions focus on confirming the assumed diagnosis, ignoring other aspects and possibly resulting in inappropriate measures. The interviewees confirmed that for all these decisions experience is beneficial in addition to acquired knowledge. The challenge lies in dealing with each individual situation appropriately.

The results of the study are reflected by the work of Møller et al. [21], in which most dispatchers emphasize that their medical knowledge and experience are the critical factors in their emergency management decision-making.

3.2 Requirements

Based on the results of the qualitative study, requirements are derived in order to create a concept for a useful case-based support for emergency call handling.

(R1) Response Time: Due to the time criticality, the proposals for a disposition decision should be in less than a few seconds.
(R2) Precise Decision: The proposed decisions should be precise or a hint should be given to the dispatcher on how to refine the query.
(R3) Flexibility: The order of the information entered into the system is not prescribed and a changed order does not affect the resulting decision.
(R4) Support: The proposed decision is not prescribed, but can be changed by the dispatcher.
(R5) Minimize Fixation Errors: The case-based component should not only output one result in case there are alternative ones.
(R6) Complex Case Representation: The case representation should be able to include several data types, such as numerical or taxonomical values.
(R7) Unknown Values: As unknown values are common, they should not have any effect on the result.
(R8) Unknown Diagnoses: Unknown diagnoses should be supported through finding similar ones from the past.

4 Case-Based Support for Emergency Calls

The overall proposed concept, which was developed based on the previously described requirements, is shown in Fig. 3. The main objective is to reliably propose measures and resource types based on a similar incident from the past. To this end, in case a decision cannot be proposed with high certainty at the current state of information, which means other similar cases lead to a contrasting measure than the most similar case, a partial aspect of the concept is deriving further reasonable and targeted questions about unknown information.

As initial setup of the case-based component, the case base is initialized in step 0 through transferring all historical emergency calls that are available in the knowledge graph to the chosen case representation. Steps 1 and 2 indicate the standard communication between caller and dispatcher, where the dispatcher asks questions in order to obtain information from the caller. The dispatcher enters this information into the emergency call handling service, which persists all data in the knowledge graph (see step 3). In the fourth step, the case-based component accesses this information and transfers it to the chosen case representation (see Subsect. 4.1), initializing the query. This can be done at any

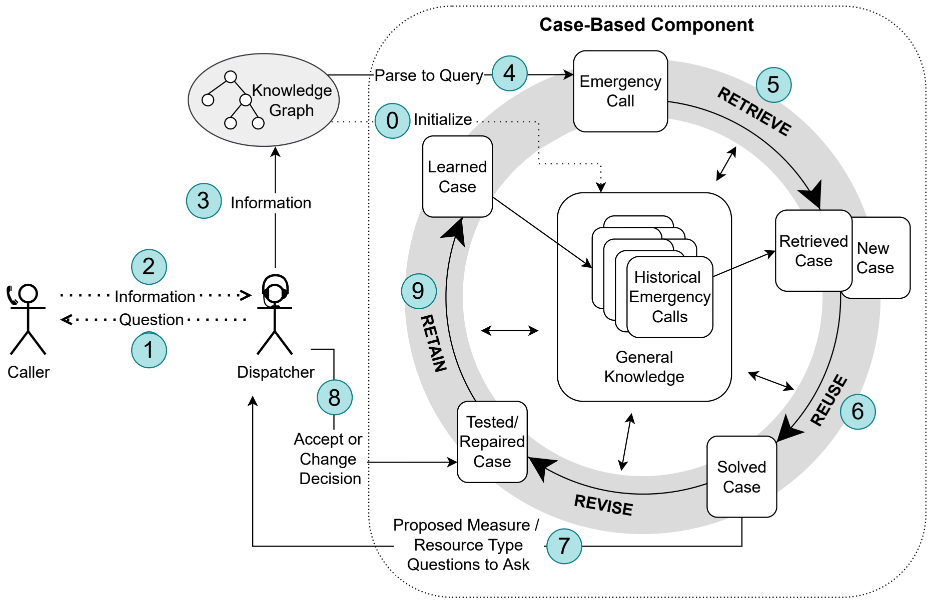

Fig. 3. Concept for a Case-Based Support for Emergency Call Response

time, but it is reasonable to await a minimum state of information, such that the results are meaningful, rather than initiating the retrieval with the first information such as name of the caller. Afterwards, the CBR cycle begins. First in step 5, the most similar cases to the query are retrieved from the case base (see Subsect. 4.2). These cases are compared to the query and decisions are derived with the overall goal of reliably proposing a measure and resource type (see step 6), which is described in Subsect. 4.3. These suggestions are presented to the dispatcher in combination with questions that could be asked in order to increase the certainty of the decision (cf. step 7), which is explained in Subsect. 4.4. The revise phase is done manually by the dispatcher, who either accepts the suggested decision for measures and/or resource types or declines them and decides for something else (see step 8), addressing requirement **R4**. In the last step, when the emergency call is terminated, such that measures are chosen and resources are dispatched, this completed case can either be retained in the case base or be discarded. In case the dispatcher chooses to ask for more information, the cycle is triggered again, starting in step 4 with an enhanced query.

The focus of this work is on retrieve and reuse. Revise and retain were not elaborated beyond the abstract description above, but are part of future work.

4.1 Case Representation

The input data for the case-based component is transferred from the knowledge graph as instances. While some attributes are stored in the cases as references to their elements in the knowledge graph, other attributes are translated into a data structure that can be used for a meaningful semantic comparison such as numerical values or address data, referring to requirement **R6**. Therefore, these instances are parsed into an object-oriented representation. In this paper, not all details of the case representation are introduced, but selected parts are explained to get an overview and some detailed insights.

One case represents one incident. There is no explicit differentiation between case and solution, but the case itself contains the solution, as it depends on which information is specified, which information is the solution. If no measure is specified, then the focus is on identifying a measure in combination with resource types. If a measure is specified, then only resource types are derived.

One `incident` contains the following elements:

- Incident Type ∈ {*Fire Operation, Medical Operation, Traffic Accident, Hazardous Substances, Person in Predicament, Other Operations*}
- Number of Affected Persons
- Set of Affected Persons
- Set of Affected Objects
- Position
- Date and Time

The main attributes on the top level are specified on the basis of the concepts in the knowledge graph mentioned earlier in Fig. 2, such as `affected persons`. Additionally, some other specific and relevant information is stored in the `incident` object, such as `incident type` or `position`. The attribute `incident type` is used for a categorization of the incident. The `position` attribute is stored as geocoordinates. In case the caller provides an address of the incident, it is translated to geocoordinates as those can be meaningfully compared.

As the affected person plays a special role, when considering medical cases, a detailed description is provided. One `affected person` is constructed as follows:

- Age
- Gender ∈ {*male, female, diverse*}
- Vital Signs
- Suspected Diagnosis

The same strategy was followed for this object as for `incident`. Some attributes are mapped explicitly due to their importance. For instance, `age` and `gender` are a decisive aspect for the suspected diagnosis [13] and are therefore specified explicitly. Here, `age` is parsed into a numerical value for a more sophisticated comparison, whereas `suspected diagnosis` is stored as reference to the instance in the knowledge graph. `Vital signs` is stored as boolean and is translated from the existence of several attributes in the knowledge graph, such as breathing, pulse or consciousness. If none of these are available, the attribute is set to false and an immediate reaction with emergency ambulance is necessary.

Additionally, `measures` and `resources` can be stored as well on the level of the incident itself, but also on the level of one affected person, to ensure a mapping in case several persons are affected. On the top level, those assigned measures and resources are aggregated, because for larger or unclear incidents no information is existent about single affected persons.

These explicitly defined attributes do not account for all possible details in the conversation. Due to the variety of information, it is also not reasonable to map everything explicitly. However, it must be assumed that all information in an emergency situation has an influence on the measure or resources and therefore, all information provided by the caller should be taken into account and processed by the case-based system. To this end, a `set of additional information` is introduced in both objects, `incident` and `affected person`, which contains all information that is not explicitly mentioned as attribute. Each element in this set is defined as key-value pair, that contains the concept ID and the instance value in the knowledge graph. All remaining information that is connected to the incident or an affected person in the knowledge graph is stored in this set.

During parsing of the incidents that are contained in the knowledge graph, several cases are created. For each incident one case is created with all available information in the knowledge graph. Furthermore, if details of single affected persons are available, they are extracted and also saved as one case in order to abstract from the overall incident (see example for a query in Fig. 4). Through this, it is possible to transfer partial solutions in the sense of individual measures and resource types from incidents with several affected persons to an emergency with only one affected person. Otherwise the incident and the number of affected persons and each affected person needs to be similar to be considered during retrieval. As can be seen in Fig. 4, the division into several cases is done analogously with one incident that is used as query. Therefore, several retrievals and disposition decisions are derived for each person for whom detailed information is available and for the rest of the incident without available details.

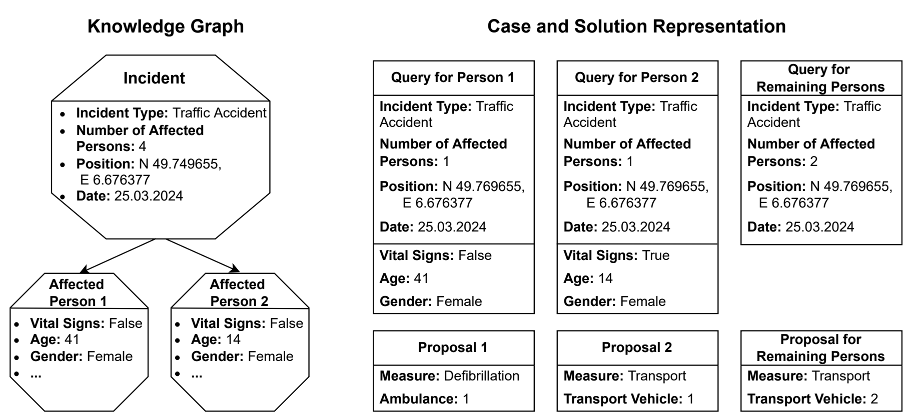

Fig. 4. Knowledge Representation in the Knowledge Graph and its Translation to Cases

4.2 Retrieve

During similarity computation, the attributes are compared according to their data type. For numerical attributes, such as `age`, a numerical similarity measure is used, that calculates the distance between two numbers and transforms it into a similarity value, where a high distance refers to a small similarity and vice versa. The time attribute is compared using the cyclic distance in order to match similar time of day. All attributes, that refer to an instance in the knowledge graph, in particular those that are arranged in a taxonomic order, are compared using semantic similarity [12]. The elements in the set of additional information are mapped to each other through using the local similarity functions. Here, the best mapping is searched for, such that if an additional information is present in both cases, the global similarity value increases. All local similarity values are provided with weights and aggregated to one global *incident* similarity.

Based on these defined similarity measures, a retrieval is performed to determine the most relevant cases for the query. The efficiency of the retrieval algorithm is one of the decisive factors for achieving a short response time due to the time-critical nature of emergency call response, addressing requirement **R1**. A suitable method that can be well applied to the concept is MAC-FAC retrieval. MAC-FAC stands for "Many Are Called - Few Are Chosen" and is a two-stage retrieval approach [10]. The MAC stage consists of a preselection that is done through an efficient similarity assessment. In the presented concept, the case base is searched for cases, that have the same value for `incident type`, while other attributes are not considered at all, as these cases differ rather than those of the same incident type. In the second stage, the FAC stage, the selected cases are sorted in descending order of similarity to the entire query with all its information. Here, we chose to determine those cases that have a similarity value with a maximum variance of 5% of the highest similarity value in order to prevent fixation errors and include other options depending on the further development of the information situation.

Furthermore, we included a weighting of attributes depending on the type of incident, as certain information has a higher influence on the measure and resource type, for e.g. *traffic accidents*, the position can indicate the severeness of the crash, like a busy intersection with potential hazards, and imply the need for stronger rescue equipment. For individual medical emergencies the age, gender and suspected diagnosis is of higher relevance.

Another important aspect of comparing cases in the emergency domain as sketched before is that there are many possible attributes and many unknown attribute values. Here, we apply the strategy of excluding values in the similarity assessment for addressing requirement **R7**, as an optimistic or pessimistic strategy would distort the global similarity value.

4.3 Reuse

As described before, those cases with a similarity value with a maximum variance of 5% of the highest similarity value are selected for reuse. As solution for the dispatcher, either measure and resource type or, if the measure is already available in the query, only the resource type of the most similar case is proposed.

In some cases, adaptation is necessary. We identified some straightforward rules that are applied. One aspect that was mentioned in the interviews where future situations can learn from historical cases was re-disposition, which means that initially too few or inadequate resources were sent, such that at a later time, additional or other resources had to be dispatched. These situations are implicitly covered by the used data structure, as there are no timestamps for when resources were sent, but only the total amount of dispatched resources are stored. Thus, if a case is reused, the total amount of resources is directly adopted without knowing if it was a result of a re-disposition in the past.

One simple adaptation rule that is applied concerns the amount of resources, as for each affected person one resource should be sent. For instance, in case of a traffic accident with a number of affected persons that differs slightly, but the rest of the case is highly similar, the resource types are adopted, but the number of resources is adapted accordingly.

Another adaptation rule prevents under-disposition. If the vital signs specified in the query are false, such that not all vital signs of the affected person are given, but the vital signs in the retrieved and most similar case are true and no emergency service vehicle or a rescue helicopter was dispatched in that case, then the reused resources are overwritten through either an emergency ambulance or a rescue helicopter. This rule is derived from the dispatcher aid of the Kaiserslautern Integrated Control Center [25], which describes, that threats for vital signs always require an emergency physician.

4.4 Deriving Relevant Questions

Furthermore, it is analyzed how certain this proposed decision is according to the available historical cases, referring to requirements **R2** and **R5**. Therefore, all cases in the retrieved set of cases are used for validating the decision, which means it is checked whether all cases share the same measure and resource type. If this is not the case, then the decision might be altered if more information is available. An example for such a situation is shown in Fig. 5. Here, three cases

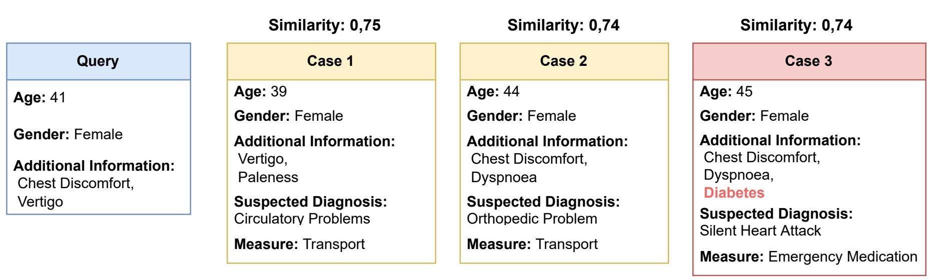

Fig. 5. Retrieval with Similar Cases and a Decisive Information

are retrieved with almost the same similarity value, but differing measures. If the most similar case would only be consulted for a disposition decision, an under-disposition might happen. However, the given information whether diabetes is present would lead to an unmistakable decision according to the cases. If the affected person suffers from diabetes, this would indicate a silent heart attack and an emergency medication is necessary. Otherwise the diagnosis would be far less severe and a transport would be sufficient.

To this end, we propose a mechanism that is applied for deriving attributes with so far unknown values in the query, that might be decisive for a decision. Through identifying relevant questions, the proposed approach is extended to a conversational CBR (CCBR) approach [2]. Here, the dispatcher decides whether to ask further questions and subsequently triggering the case-based component again in order to support the decision, in contrast to traditional CCBR approaches, where the systems decide by themselves whether to stop asking for more information and propose decisions. Therefore, the following steps are made:

1. Identify the goal of decision which is either the measure or resource type in case the measure is already specified in the query.
2. Evaluate, whether this previously defined goal differs in the retrieved cases. If not, the decision based on the cases is certain and no attribute to question is proposed.
3. Otherwise identify all attributes, that are unknown in the query, but specified in one of the cases.
4. Apply an attribute selection strategy for all these attributes considering the goal of decision.
5. Propose this identified attribute to the dispatcher to ask the caller about its value in order to increase the certainty for the decision.
6. If the dispatcher decides to ask about the attribute value and obtains a new information, the retrieval is triggered again for a revision of the proposals for a disposition decision.

Several existing strategies could be applied for identifying the attribute that allows for a more efficient discrimination of similar cases and thus, increase the certainty of the decision. Some first ideas are sketched in the following.

An established measure from information theory that could be applied is the entropy that could be assessed for each attribute [23]. Through this, the expectation of the information gain of a known value for an attribute is measured.

Kohlmaier et al. developed an approach specifically for CCBR that utilizes the similarity influence of an attribute in order to determine relevant information [14]. Furthermore, McSherry proposes a lightweight local feature selection strategy based on n similar retrieved cases through computing the discriminating power of one attribute in the medical domain [19]. Which strategy fits the domain of emergency call handling best and which small adjustments are necessary, needs to be evaluated in future work.

While requirements **R3** and **R8** were not considered until now through integrating specific aspects in the concept, they are met through the case-based approach itself. Requirement **R8** is addressed through using the concept of similarity that is able to assess similar results, rather than rules that are hardly able to allow vagueness. Furthermore, requirement **R3** is implicitly met through the case representation that does not take any temporal dependencies into account, such that the order of inputs has no effect on the outcome.

4.5 Prototypical Implementation

The concept is prototypically implemented with the process-oriented case-based knowledge engine ProCAKE [7]. The knowledge graph is integrated as additional knowledge that is used for computing the semantic similarity. ProCAKE itself is connected to the SPELL platform through an implemented API that can receive and send data. This implementation was used so far as proof-of-concept, while all requirements could be met at least partially. For this, we modelled several exemplary emergency calls as cases in cooperation with experts and simulated different aspects of the concept. Nevertheless, an evaluation of utility with the rating of experts remains open and will be addressed in future work.

5 Conclusion

In this paper we presented an approach towards a case-based support for emergency call handling, that proposes measures to be taken and resources to be dispatched. Furthermore, we described a mechanism to provide information to the dispatcher about what question to ask to increase the certainty of the proposed decisions. Moreover, we sketched the pursued hybrid AI approach towards integrating rule-based and case-based reasoning for emergency call handling. The presented work focused on the technical implementation of the case-based decision support. In future work we plan to investigate the necessary reconciliation mechanism for this hybrid AI approach in case both single approaches deliver different results.

A so far ignored aspect is the acceptance and trust of the dispatcher. Therefore, a further focus will be laid upon an adequate visual integration of the decision proposals in the existing user interface of the rule-based emergency call handling. To this end, the mental workload of the call-taker should be at the center of attention in terms of not overloading but focus on the most important information with explanation in order to increase trust [15].

Besides, the prototypical implementation of the approach will be evaluated in real scenarios with experts that simulate an emergency call handling process.

So far, the approach mainly focused on medical emergencies. A possible transfer of the proposed approach to non-medical emergencies, such as firefighting-related ones, will be investigated.

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