# Towards Data Awareness by Socio-technological Knowledge Management

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Abstract: In today's data-centric world, the data-awareness challenge is a crucial touchstone to existing knowledge management technologies. Adaptive, stakeholder-centric knowledge modelling approaches provide a solid ground to tackle this challenge and open the door to enrich knowledge management by a socio-technological perspective. This paper proposes the use of a socio-technological approach to overcome the data-awereness challenge by treating knowledge on data as a crucial business asset. Here, a data awareness generating, iterative, incremental knowledge elicitation technique based on a multi-perspective, multi-modal diagrammatic knowledge representation language serves as proof of concept.

## 1 INTRODUCTION

Data-driven software systems and data-based analyses are the engines of today's innovative businesses. The key to start and operate such an engine is the awareness an organization and its individual stakeholders have of their data, its context and meta-data as well as the corresponding implicit background knowledge. Establishing this data-awareness and addressing the awarenss challenge requires knowledge management (KM) to treat knowledge *on* data – and not only data itself – as crucial business asset.

**Thesis.** Data awareness within an organization – in the sense described above – can only be established when a socio-technological perspective on the involved stakeholders is included. Thus, we need to rethink knowledge technologies and methods to (self-) adapt to the needs of the individual stakeholders and their multiple views, and not the other way round.

**Setting.** Knowledge assessment in an enterprise setting requires to make knowledge on existing data, data sources, corresponding meta-data on data quality, and the related context knowledge. The results are tangible knowledge shared by the whole organization for all participating stakeholders, e.g. from management over IT to physical, industry workers – thus, deriving an overview over the "data landscape". Each stakeholder represents different domains and functions and has an individual perspective on the data, including its context, that is processed by a system. The acceptance of a system depends on how well the system is capable of reflecting the different user priorities and perspectives and of facilitating knowledge sharing among the stakeholders.

Knowledge elicitation as part of the requirements analysis phase when developing next-generation data-(& knowledge-)based enterprise information systems, e.g. in the context of Industry 4.0, should therefore extend its mindset as well as its applied methods and tools, to include a socio-technical perspective. Existing methods and tools – such as UML or BPMN – cover mostly the specification and documentation of software systems and processes. What is needed, is thus the conception and specification of a method that fit precisly into the required spot: a socio-technical enbabled method to establish data awareness as part of the requirements analysis phase. Establishing data awareness is a multi-disciplined task, where exchanged knowledge must be accessible to all stakeholders. As data-(& knolwedge-)based information systems are rarely developed on the green field, we need to underpin their architecture and design with sufficient knowledge on the structure of existing data, thus making the implicit knowledge (also hidden in an organization's hierarchy) and legacy knowledge accessible for system engineers and data analysts as well as software developers.

Crucial for the success of knowledge management techniques is the provision of access to implicit background knowledge on various hierarchical levels in the business organization, and the possibility to easily adapt to each stakeholders' context and the peculiari-



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ties of the domain. In our view, this holistic view on data awareness is a critical contribution to ensure the acceptance of data-driven systems to be developed.

**Note on Awareness.** We utilize the term "awareness" close to its psychological understanding as "perception or knowledge of something" and achieving accurate reportability of the perceived process (APA, 2019). We apply awareness both regarding the stakeholders' understanding and their self-perception in the model itself and the underlying context.

This paper presents an approach using a socia-technological perspective to establish data awareness. This buttom up and self-adapting approach consists of a three-step description for involving all participating stakeholders and a notation for data modelling. The reminder of this paper is organized as follows: The awareness challenge is further outlined in Section 2. In addition, a review of existing approaches to multi-perspective modelling is given. The proposed method is presented in Section 3 and conclusions are given in Section 4.

## 2 AWARENESS CHALLENGE

We argue that the KM community must devise their next generation of knowledge management techniques to inherently by design tackle the awareness challenge. A technique to be proposed consists at least of a method to elicitate and maintain knowledge based on a corresponding knowledge representation language. The challenge can be narrowed to the following set of requirements to such a technique:

- It shall address and adapt to multiple stakeholders with different perspectives on different organizational layers (viz. Fig. 1);
- the underlying representation language shall be both formal & sound, and thus open to algorithmic treatment, but also
- shall be easily accessible to the stakeholders, as accessibility is key for generating awareness;
- the formalism shall interweave data, meta-data, infrastructure and process models;
- the elicitation method shall be "minimal invasive" and not disturb the business and disquiet the stakeholders in their natural habitat;
- hence, a technique shall embed itself into organization and shall be suitable for everyday use;
- but shall also focus awareness from the point of view of each of the individual stakeholders, i.e. adapt to each stakeholders individual desideratum;
- existing knowledge frameworks (e.g. process maps, descriptions of IT infrastructure, etc.) shall be sufficiently included or interfaced as far as appropriate;
- the formalism shall bridge the gap between (possibly existing) formally described processes and the way it is instantiated, i.e. lived, adapted and adopted, always anew in everyday business;

Measuring awareness itself and thus evaluating a solution to the awareness challenge is a scientific barrier. We assume in the following, that a higher awareness leads to a better quality of the underlying business process, which is slightly easier to measure.

**Regarding Existing Solutions.** Existing approaches on multi-perspective modelling, e.g. (Wood-Harper et al., 1985) (Curtis et al., 1992) (Stohr and Zhao, 2001), fix to certain set of perspectives regarding a special application domain and often neglect accessibility by all participating stakeholders. Putting the stakeholder in the center of modelling, e.g. as in (Jablonski, 2009), often leads to restrictions in expressivity and readability.

The UML standard offers a range of diagrams as notation for multi-view artefacts, which can be further formalized with profiles and viewpoints (Object Management Group, 2017). However, these extensions to UML are rather used to formally capture information from spezialized domains, with current research on multi-view notation and their consistency (Cicchetti et al., 2019). Instead, a new formalism is needed that focuses on accessible views for stakeholders with different background and level of operation.

More business artefact targeted approaches like artifact-centric process modelling (Nigam and Caswell, 2003) (Bhattacharya et al., 2007) (Kumaran et al., 2008) (Cohn and Hull, 2009) miss multiple perspectives and often focus solely high-level management stakeholders.

Merging process and data modelling pari passu is still extremely rare, e.g. (Künzle and Reichert, 2011). Several approaches focus on a data-centric view on business processes (Sun et al., 2006) (Aalst et al., 2015), (Deutsch et al., 2009) or anticipate an object-aware process support (Reichert and Weber, 2012), (Künzle and Reichert, 2011). Other data-centric modelling approaches research knowledge awareness in process-aware information systems (Bhattacharya et al., 2009) (Reichert and Weber, 2012). Although both UML and BPMN (Object Management Group, 2013) offer the coexistence of process and data-related elements, the two conceptual models are rarely formally related and used separately by different teams (De Giacomo et al., 2017). More recent approaches formalize the connection between process and data, especially between BPMN and UML activity diagrams with a "conceptual view" (Combi et al., 2018a) (Combi et al., 2018b). Nevertheless, most approaches only seem to provide a complicated fix to existing modelling languages by reducing their readability, and are, thus, rather far from being applicable in an everyday setting.

Modelling frameworks often provide a toolbox of different approaches and strategies to adapt to rather different application domains and groups of stakeholders. However, they require to be introduced top-down with support from an organizations higher level hierarchy, substantially influence the daily business (thus are rarely minimal invasive), and do not focus individual stakeholders and their demands. Though, these frameworks often address a lot of the other requirements of the awareness modelling challenge. For example, ArchiMate (Lankhorst et al., 2009) emphasizes communication with the stakeholders and a multi-viewpoint modelling approach; however, viewpoints are restricted to a stakeholder group and the target is not a holistic model. Also ArchiMate trades flexibility for formalization and ease of use. Further, these frameworks need to be established top-down in an organization – often not in a minimal invasive manner. This is another hurdle for assuring the participation of all stakeholders and their awareness. Similar objections would hold for other well-established major frameworks like IDEF (Bruce, 1992), TOGAF or IAF (Wang et al., 2016), or ZF (Zachman, 1987).

Supposing accessibility as key to awareness, most notions of accessibility in practice are boiled down to cognitive effectiveness or even only readability. However, accessibility rarely played an initial principal role in the design of state-of-the-art established modelling languages like UML or BPMN (Reijers and Mendling, 2011) (Moody and van Hillegersberg, 2008) (Störrle and Fish, 2013). Moody's "The Physics of Notations" (Moody, 2009) has proposed a catalogue principles that target this shortcoming and includes several ideas how to devise a syntactically based and measurable notion of accessibility. This catalogue should be taken seriously from the start when devising a knowledge representation language.

Thus, resolving the complete data awareness challenge with existing approaches is not straightforwardly possible; especially, as existing approaches in their practical implementation often mainly focus the business-technological side that is established in a top-down manner, and not the social embedding of the stakeholders, i.e. their self-awareness and long-term established accountability and responsibility regarding a concrete business process and the corresponding data. Existing frameworks often provide a bouquet of different techniques, diagrams, methods, etc., to be combined into a set of knowledge tools that are tailored to a concrete domain. However, these frameworks and their a priori chosen set of tools not easily adapt on-the-fly to the stakeholders' needs and in general do not focus data awareness as central concern.

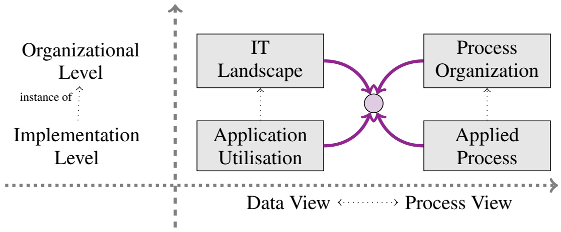



Figure 1: Combining a data and process view in one dimension with hierarchically different granularity due to different systemic levels, we target a sweet spot ("") for multi-perspective modelling.

**Knowledge Management 4.0.** Recently, there are several tendencies to re-invent knowledge management in the context of current technological trends and in the setting of Industry 4.0, e.g. (North and Maier, 2019), (North et al., 2018), or (Peinl, 2017). These are similar in spirit to our approach but focus on generic, top-down business perspective, whereas we primarily take a socio-technological, awareness-focussed angle.

**Proposed Path to Tackle the Challenge.** Inspired by the well-established design principles of "keeping it simple" and leaving out parts that "you aren't gonna need" (KISS & YAGNI), we tackle the data awareness challenge by a "bottom-up" approach, starting from the concrete participating stakeholders and their embedding in a business process, as follows:

- A diagrammatic, multi-perspective modelling language that is implicitly accessible to all stakeholders, can be represented sufficiently formal, and is embedded in
- an iterative, incremental elicitation method, supporting the generation of (data) awareness, combined with
- a self-adaption along these iterations of the both language and method itself in a concrete knowledge management situation.

This three step approach helped us to bottom-up derive a diagrammatic modelling language that, embedded in a suitable knowledge elicitation method, helped us to establish a data awareness in a practical setting – thus, providing a proof of concept that the awareness challenge can be tackled by taking a socio-technological perspective on knowledge modelling, elicitating and maintaining.

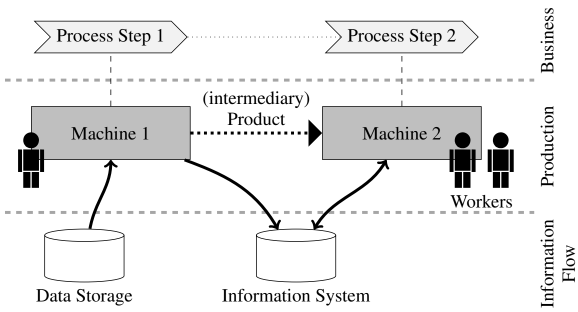



Figure 2: Running Example's simplified Industry 4.0 production context: different layers & perspectives.

# 3 PROOF OF CONCEPT: DATA-AWARE MODELLING

We briefly present the diagrammatic knowledge representation language devised by following our path to tackle a concrete practical instance of the awareness challenge. We applied this multi-perspective language in a series of elicitation interviews to successfully establish a notion of data awareness among all participating stakeholders.

**An Exemplary KM Application.** In a recent information systems engineering project, two of the authors faced the task of creating a process-spanning data-inventory in a manufacturing facility in order to be able to design data analysis applications in the context of enterprise systems. We experienced, however, the difficulty to harmonize the specific information from the perspectives of different stakeholder groups, e.g. workers, process managers and data analysts. This problem matches the information gap in the existing perspectives, as we could analyze the information provided by the different stakeholder groups separately but we could not make them accessible for a joint understanding and could not integrate them into a holistic model. At its core, this situation is a prototypical instance of the awareness challenge, with additional intricacies belonging to the manufacturing domain (e.g. only semi-digitalized data, strong hierarchical dependencies between the stakeholders,...) – these will be left out in the following discussion.

Exemplarily, a generic Industry 4.0 production context is represented by Figure 2: A two-step production in the physical world is based on preparing a physical product on Machine 1, which is then moved to and further processes on Machine 2. Both machines are operated by Workers and are embedded into an IT landscape, e.g. reading machine parameters from a database and exchanging information via the ERP system. Without loss of generality, we assume in the following that each process step runs on one corresponding machine and that each machine is operated by one worker. Further, we restrict ourselves to processes that are chain-like and step-wise (e.g. no forks, alternatives and joins). However, the presented approach can be straightforwardly generalized to cover these more complex process models.

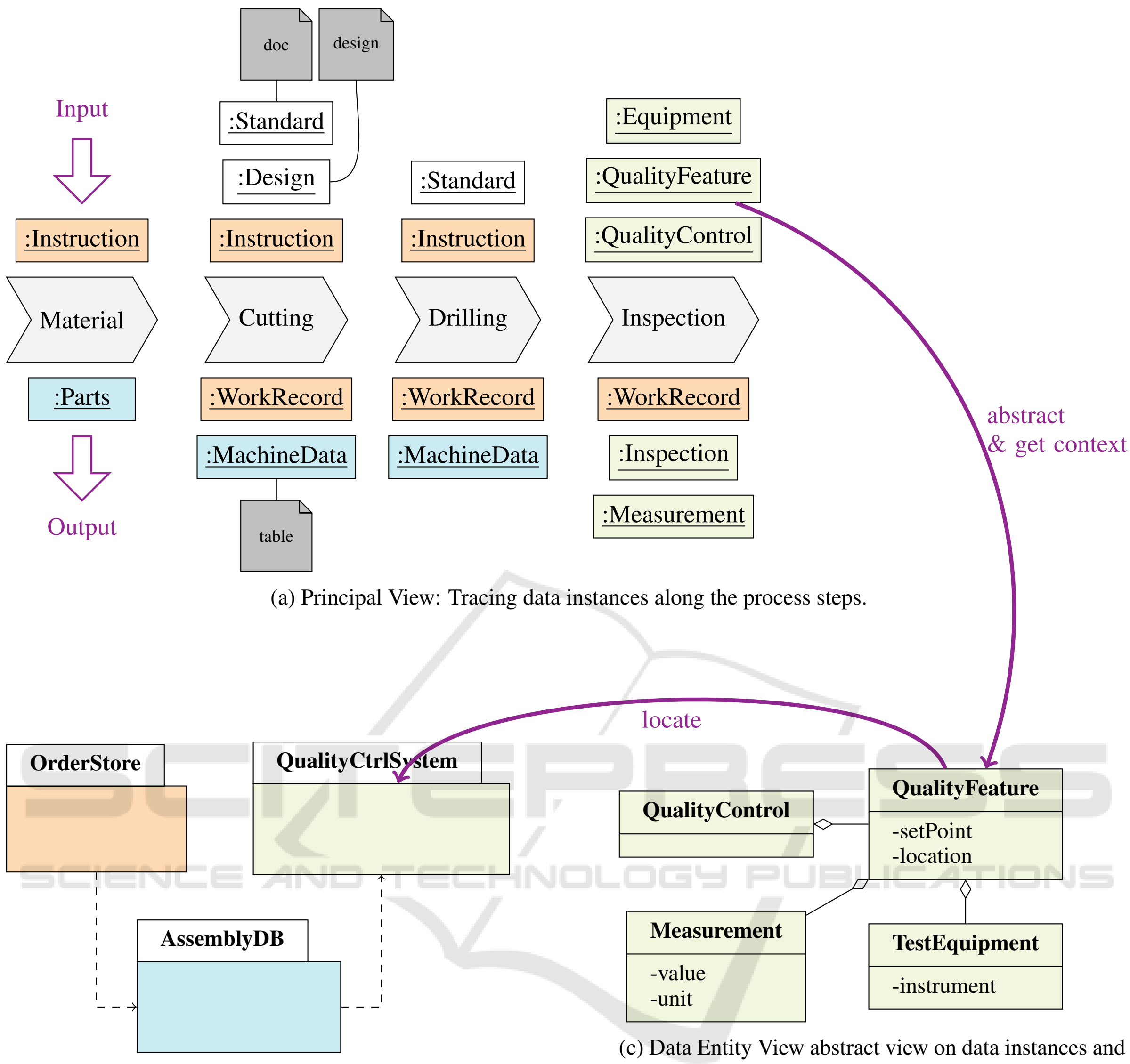
We refer to concrete data objects that are accessed in a single instantiation of the process, i.e. producing one concrete product, as *data instances*. Examples here are a paper job card that is tracking what takes place in the production process or machine parameters that are taken from a data base.

**Data Awareness Analysis Diagrams.** The core of our approach is a diagrammatic modelling language, called Data Awareness Analysis Diagrams (DAAD), that served as a medium for discussions with the different stakeholders. DAAD was derived pragmatically in practice and it is based on a combination of distinct (formal) diagrams. We provide sufficient formality for this notation derived from practical needs to see its connection with existing, competing formalisms. A rigid formalization of the diagrammatic formal language is currently in preparation.

Inspiration for DAAD was certainly drawn from the broad background of diagrams applied in software engineering and in the stakeholders's daily work practice. Hence, reminiscences to UML class, object, package and use case diagrams as well as business process modelling languages are implicit but were initially not explicitly intended, as the notation grew from a pragmatic need and was not a priori designed in a purely theoretic setting. Further, to cover the needs of a multi-perspective, i.e. holistic, view, we adapted the $4+1$, or better $n+1$ architectural view approach of (Kruchten, 1995) to our needs, by orbiting a central diagram with a set of additional "perspective" diagrams related to the different views of distinct stakeholder groups.

To simplify the presentation, we will not draw a distinction between the view or perspective itself and its representation in the corresponding diagram in the following and will not distinguish between the abstract and concrete syntax of the diagrams.

**Principal View.** In the following, we present these views inside-out by starting with the central Principal View. The Principal View combines a data-oriented with a process-oriented view, and "floats" between the organisational and the implementational level, as introduced in Figure 1. Thus, this view can be seen as the nexus of the knowledge elicitation interview technique. While the Principal View serves as the main communication anchor for operational users, the sur-




(a) Principal View: Tracing data instances along the process steps.

(b) Data Architecture View: Relating data instances to the storage architecture.

(c) Data Entity View abstract view on data instances and their relations.

Figure 3: Example DAAD. We only present an excerpt containing three prominent perspectives. Color is applied to connect entities between the different views, e.g. the QualityFeature data instance is subsumed by the QualityFeature class that can be found in the Quality Control System in the IT landscape. Different stakeholders can insert their background knowledge in their "closest" perspective. Then, the other perspectives are updated accordingly. Taking the view from a different perspective supports any stakeholder to reconsider their position in the underlying business operation and, thus, to gain additional self-awareness besides the data awareness.



rounding views are pivotal for bridging adjacent domain areas.

Supposing a step-wise representation of the underlying production process, the basic unit of the principal view represents one of these steps by the symbol ▷ and relates the data instances accessed in this step. Each ▷ can include additional information, e.g. an identifier, or description of the machinery used. We differentiate data instances that are read by actions in this step, i.e. its input, and those that are written, i.e. its output. We depict the input instances above ▷ and the output instances below. See for example the "Material" step in Figure 3a: Instructions feed into the Material-▷ and we output (a collection of) parts. Data instance that are updated, i.e. both read and written, appear both above and below of ▷, whereas the identity is assured by assigning the same instance identifier. We resort to depict these data instances similar to object in UML object diagrams. Thus, we can also add additional information, e.g. example documents or screenshots of the user interface to the corresponding data instances. These data annotations build a visual bridge between process and entity elements for stakeholders from the process domain.

In the Principal View, we now combine different steps along a temporal axis to sequentially represent the underlying production process (see Figure 3a: step sequence from "Material" over "Cutting" and "Drilling" to "Inspection"). As before, anonymous objects depict different data instances of the same type along the process chain, while data instances using the same identifier (not shown here) represent the same data object. For example in Figure 3a: The "Instruction" and "WorkRecord" data from the first steps are from the same IT system. Recall that without loss of generality we assumed these processes to be linear, i.e. chains, only. Hence, we put the linear sequence of in the center of the diagram from left-to-right.

**Adding Additional Perspectives.** Covering the principal information regarding the interaction between data and the (business) process and, thus, aiming at the heart of the information gap, we enrich the Principal View by different additional, stakeholder-driven perspectives. Thus, we provide access to the system parts mentioned in Figure 1 through intermediary views that refer to elements of both the Principal View and the existing enterprise information system. For simplicity, we rely on the (UML-inspired) diagrams already established and applied in each stakeholder's domain as far as possible to assure readability and accessibility:

**Data Architecture View.** We provide an UML package diagram with additional meta-information to represent data context groups on an abstract level. The groups can be UML-ish packages or class stereotypes and are associated with a simple coloring scheme. This view is presented to IT and relates the context groups to their concrete location in the underlying IT landscape, e.g. servers, information systems, databases. The coloring scheme is used throughout all views to re-identify the context groups.

**Data Entity View.** An UML class diagram is used to detail the data context groups. The Data Entity View provides the data analyst with a detailed view on the processed data from a abstract conceptual perspective. See Figure 3 for an example.

**Data Characteristics View.** Additionally we provide the data analyst with data characteristics, derived from the V's" of Big Data (Gandomi and Haider, 2015; Sagiroglu and Sinanc, 2013), represented in an appropriate formalism. The choice of this formalism heavily depends on the analysis framework to be applied later on in the engineering process. In our case, we applied a simple table assigning "V"-qualities to types of data instances with the help of a table.

**Process View.** The Process View provides a business process language representation of the underlying process. However, in our context, the representation by the chain of already included in the Principal View was sufficient to represent the perspective from process management.

**Business View.** The Business View embeds the information contained in all other perspectives, and especially from both the Process View and the Data Architecture View, into high level business perspective in form of an UML Use Case diagram. This permitted us to embed the process and data/architecture perspective into the organizations management context and to highlight the participating stakeholders and their connection in the business case underlying the production process; thus, providing a general and very abstract anchor point for all gathered information. The Business View also embeds the whole endeavor in the underlying information system development's requirement analysis model and provides reference points for traceability.

Additionally, we harmonized the different perspectives by making the connection of elements between them visually explicit, e.g. by using the same color representation for instances and the corresponding class. This allowed us to provide a straightforward traceability of concepts between the different abstraction layers. For example, one could easily match a data instance `:QualityControl` in the Principal View with its class's data context group in the Data Entity View and thus the corresponding IT system where this instance is maintained/stored in the Data Architecture View by tracing the instance's color.

Thus, the diagrammatic modelling language DAAD is the spearhead of our approach that targets the data awareness challenge via its embedding in an iterative, incremental knowledge elicitation method.

## 4 CONCLUSION

Posing data awareness as central concern of knowledge management proves to be a challenge to both existing formalisms and techniques. Taking a socio-technological perspective and a bottom-up self-adapting approach supplies sufficient tools to tackle this challenge in concrete practical situations. Here, we provided a proof of concept regarding a newly devised modelling language in an industry 4.0 domain that embraces data awareness as central concern.

Beyond the presentation here, we supplied the modelling language with a proper formal foundation and were able to show, that it shares semantic similarities with UML but gains better accessibility in general. A formalization of updating and harmonizing multi-perspective models in DAAD and tool support is planned as future work. Further, we are still augmenting the language to cover practical demands in data-analytical business processes, e.g. including context information (as crucial for sustainable data-analyses) and classical organizational knowledge models in addition to data and process models by additionally embracing knowledge maps (Eppler, 2001) as additional perspective. Seeing the success of the bottom-up derivation of a self-adapting knowledge representation formalism, we want to investigate further the direction of modelling frameworks that embrace at their core a notion of on-the-fly self-adaption to concrete stakeholder demands.

Future work will also include the transfer of DAAD to other domains and apply the three-step approach to tackle the awareness challenge in other practical knowledge management application situations. This will serve the long term sustainability and development of DAAD.

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