Knowledge interoperability and re-use in Empathy Mapping: an ontological approach

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Abstract

Design Thinking is a human-centered approach extensively used across different domains that aims at problem solving, value creation for stakeholders and innovation by fostering creativity. The most characterising and critical step along the Design Thinking process is the empathy phase, in which stakeholder analysis is performed by looking at a given scenario from the perspective of different stakeholders. Such a methodology enables a systematic information gathering and organization that results in a deep understanding of actual problems, needs and expectations from the target stakeholders. The uniqueness of problems and the need for situation-specific data makes knowledge re-use not always practical, even within the most consolidated and experienced environments. In this paper we propose an ontological support to empathy mapping that aims to (i) establish an interoperable fine-grained data layer among the different data collected throughout the empathy mapping process, (ii) enable multi-scenario analysis underpinned by formal specifications and (iii) further empower the process through semantic enrichment and integration of insight from multiple sources and contexts. We believe this is the first step to design and properly integrate effective computational and AI-based functionalities along the creative design thinking process, as well as to enable in practice richer and more sophisticated approaches (e.g. through social networks).

Keywords: Ontology, Data Integration and re-use, Semantic Interoperability, Semantic Web, Data Engineering, Knowledge Engineering, Design Thinking, Empathy Mapping.

1 Introduction

Design Thinking [Brown et al., 2008,Dorst, 2011] is a human-centered approach extensively used across different domains [Johansson-Sköldberg et al., 2013] that aims at problem solving, value creation for stakeholders and innovation by fostering creativity [Kolko, 2018]. Design thinking frameworks are currently applied in a number of disciplines other than the classical business context [Davis, 2010], such as, among others, social innovation [Brown and Wyatt, 2010], healthcare [Roberts et al., 2016], software engineering [Ferreira et al., 2015a], pedagogy [Luka et al., 2014], policy-making [Mintrom and Luetjens, 2016], management [Liedtka and Ogilvie, 2011] and sustainability [Fischer, 2015]. An additional mention is for educational context, where design thinking is extensively adopted with a wide extent (e.g. [Oxman, 2004]).

The most characterising and critical step along the Design Thinking process is the empathy phase [Köppen and Meinel, 2015], in which stakeholder analysis is performed by looking at a given scenario from the perspective of different stakeholders. Such a methodology, that applies at an analysis level the well-known social concept of empathy [Stueber, 2013], aims to enable systematic information gathering and organization that results in a deep understanding of actual problems, needs and expectations from most relevant or target stakeholders.

In order to make such a process as effective as possible [Osterwalder and Pigneur, 2010], especially in a team-work and multi-disciplinary contexts [Seidel and Fixson, 2013], analysis based on empathy is normally supported by simple specific visual tools known as *empathy maps* (e.g. [Bland, 2012]).

Why interoperability and re-use in empathy mapping? Design Thinking results very effective in fact under the realistic assumption that each problem is somehow unique and, although certain principles and concepts may be generalised, situation-specific analysis and data are normally required. That is probably one of the main reasons, if not the main one, to apply empathy in order to better and deeper understand the various stakeholders in a given context. For instance, Personas at a different level of detail can be created by adopting empthaty mapping [Ferreira et al., 2015b].

However, the unique features that may characterise contexts and problems are still perfectly compliant with some kind of formalization in the context of a creative process for systems design. Indeed, existing tools for empathy mapping drive the knowledge building process by providing a more structured and consistent model of analysis. So, is the knowledge built as a result of an empathy mapping process re-usable? How? And in which extent? We believe that Design Thinking is evolving itself as a response to a continuously changing World [Bjögvinsson et al., 2012,Martin and Martin, 2009]. As recent emerging concepts (e.g. computational design, in which the classical representation is replaced by simulation [Menges and Ahlquist, 2011], and data-driven design, based on the balance between analytical mastery and intuitive originality [Martin, 2010]) show, such an approach and the major technological trends around data and computation are progressively converging.

We believe that, in such a context, the formal structure of the knowledge, both with the capability to systematically re-use and enrich it though progressive integration and refining, may play a key role in the next evolution of Design Thinking, as well as in its application to cutting edge scenarios.

Ontology and Semantic Web Addressing knowledge formalization, data integration and re-use in a context of interoperability, the concept of ontology [Guarino, 1995] becomes definitely central. Additionally, a semantically enriched data-driven environment in a context of interoperability to support and foster creativity and innovation naturally leads to the Semantic Web [Berners-Lee et al., 2001] and the Linked Data [Bizer et al., 2011] model. Intuitively, such a data infrastructure supports a relatively basic concept: everything can be potentially linked to everything across the Web under the assumption of semantic interoperability [Heiler, 1995].

In this paper we propose an ontological approach to empathy mapping implemented upon Semantic Web technologies [Cardoso, 2007].

Methodology and approach Design Thinking tools underpin a common philosophy to problem solving but may differ very much from each other, as well as they may be customised and used in different ways depending on context, extent and intent. Therefore, a rigorous approach to knowledge management based on the formal analysis of existing tools might not be effective in this case and also it could not respond to practical needs. Taking advantage of the ontological approach and of the advanced features provided by the current semantic technology, we have proposed an open and extensible vocabulary that allows a non-prescriptive approach to data structures. Since we are not proposing new tools or techniques for Design Thinking, in our humble opinion, this approach can be considered to be reasonable and doesn't imply specific risks as the core vocabulary provided is expected to evolve end be extended as the function of users needs and requirements of the different target systems.

Research relevance This research work aims to pragmatically enable the knowledge building process and the related data structures requested by the problem space analysis in Design Thinking within the Semantic Web. Such a key step potentially creates a novel environment and context for Design Thinking in which human creativity meets the most modern digital platforms as a response to a data-intensive society. It determines a number of direct and tangible implications as well as great potentialities in perspective. Indeed, from a practical point of view, the semantic approach provides the capability to progressively define and eventually describe the problem context by adopting a non-prescriptive approach supported by an extensible vocabulary which allows semantic linking at a global level. Additionally, according to a more holistic view, the ontology-based approach can be considered the ideal infrastructure to design and integrated AI-based features applying, among others, the most sophisticated techniques in terms of NLP [Otter et al., 2020] and Web data mining [Ristoski and Paulheim, 2016]. We expect a further and more consistent integration of content from online social networks to become more and more relevant in the next future [Pileggi et al., 2012] in the context of ideation processes. Last but not least, the pandemic we are currently living has pointed out and remarked the need to be flexible and adaptive in challenging conditions [Manzanedo and Manning, 2020]. A cutting edge knowledge management could definitely facilitate a consistent development in such a direction.

Structure of the paper This introductory part of the paper is completed by the following section that addresses related work. The core part of the paper (Section 3 3) provides an extensive explanation of the ontological approach to empathy mapping and of its implementation. An example of use of the ontology related to a simplified scenario is also proposed in the same section. Section 4 deals with some considerations on possible practical applications of the ontology, as well as results are discussed at a more holistic level in Section 5 looking at the next generation tools for Design Thinking. The paper ends with a conclusions section which also addresses possible future work.

2 Related Work

As far as the author knows, there are not many existing works on the topic in literature. For instance, in [Ramaprasad and Syn, 2013], the authors adopt ontology to support the evaluation of the realised design against the idealised one.

More holistically, within the business context, the ontological approach is very common to support a proper organization, structure and management of knowledge [Fensel, 2002] (e.g. [Jackson, 2004]). However, the knowledge resulting from an empathy mapping process is very specific and it would be hard to be managed in fact in a wide context. Focusing explicitly on the design process, ontologies are relatively common assets, for instance in the context of user-centered design [Negru and Buraga, 2012], and can play a role to foster or improve certain aspect of collaboration [Lee and Jeong, 2012] and even creativity [Fulea and Brad, 2011].

In this paper we propose an ontological support to empathy mapping that aims to (i) establish an interoperable fine-grained data layer among the different data collected throughout the empathy mapping process, (ii) enable multi-scenario analysis underpinned by formal specifications and (iii) further empower the process through semantic enrichment and integration of insight from multiple sources and contexts.

Ontologies have been extensively adopted to address data interoperability in a wide range of application domains such as, among the very many, network management [Wong et al., 2005], urban planning [Pileggi and Hunter, 2017], healthcare systems [Khan et al., 2014], product data management [Panetto et al., 2012] and biological and medical data [Schriml and Mitraka, 2015].

Data integration is a key step to value creation [Lee and Jung, 2019] [Zhang et al., 2020], especially in a Big Data context [Dong and Srivastava, 2013], and, more in general, creates the condition to extended analysis (e.g. [Pai et al., 2017]) and knowledge building [Hmelo-Silver and Barrows, 2008]. Finally, semantic enrichment and linking contribute to create customised environments (e.g. [Belsky et al., 2016]).

3 An ontology for Empathy Mapping

The ontological approach proposed in this paper is, at least in theory, agnostic with respect to the concrete empathy map model adopted, as well as with respect to the context in which such tools are used (e.g. classic design thinking or other processes/techniques). That is because of the ontology characteristics which allow semantic equivalences and, more in general, a valuable support in terms of interoperability, which is understood at a semantic level. If properly used, those mechanisms can assure an integrated use of knowledge gathered by adopting different approaches, methods and tools.

In order to provide a development as tangible as possible, we refer to a typical and very popular empathy map model [Bland, 2012]. Such a model is briefly explained in the next subsection. Additionally, in order to make an ontology for empathy mapping effective in practice, also the context of the problem has to be properly modelled and formally specified. As explained in the next subsection, empathy mapping is an attempt to analyse a given scenario from the perspective of single stakeholders. Therefore, the context of the problem is defined accordingly as a semantically enriched composition of interactions and facts involving target stakeholders.

3.1 Understanding Empathy Mapping in context

The context of the problem aims to provide a description as formal as possible of the target scenario. In the context of the proposed framework, it is defined according to the model represented in fig. 1, which includes three different key concepts as follows:

- *Stakeholder*. As in a common meaning, stakeholders are understood as the actors which have an interest or concern in a given context, which is object of attention or analysis.
- *Key Relationship*. It is some kind of relationship or interaction among stakeholders. The understanding and meaning may vary very much from case to case.
- *Relevant Fact*. It characterizes the scenario by providing situation-specific data and factual information. Such information normally aims to particularise a generic scenario involving stakeholder to reflect a more concrete and richer situation that include data and facts.

An empathy map (EM) is related to a single stakeholder. An exhaustive explanation of the methodology and realted processes is out of the scope of this paper. However, a self-explanatory description is provided in fig. 1 by adopting the reference model provided by [Bland, 2012].

3.2 Ontological Representation

An overview of an ontology that materializes the model previously described is proposed in fig. 2. Main classes and properties of the OWL [OWL,] implementation are reported in table 1 and 2 respectively.

The class *Problem_Context* allows the unique identification of a given context characterised by a number of stakeholders and relevant facts that can be defined by adopting the respective classes (*Stakeholder* and *RelevantFact*). Stakeholders may be related to the context of the problem by adopting a pair of inverse object properties (*composedOf* and *isPartOf*), while a given fact is related by using the object property *happens*. Additionally, stakeholders and facts are associated with each other through a pair of inverse object properties *affectedBy* and *affects*.

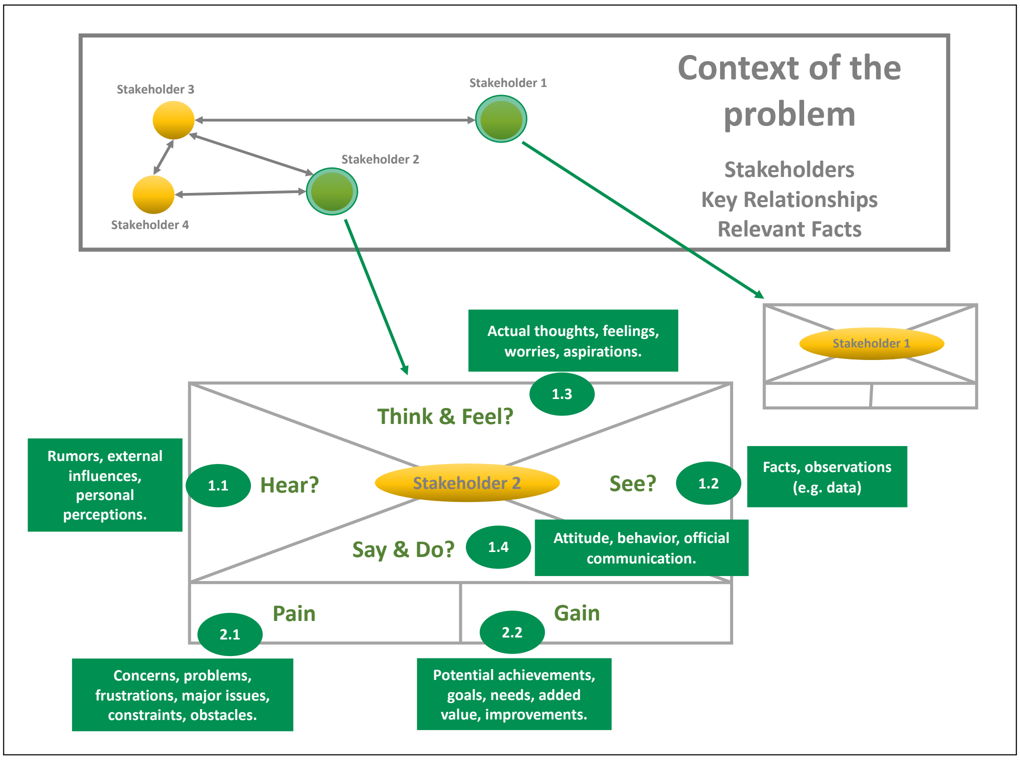


Figure 1: Typical Empathy Map [Bland, 2012] in context.

The different EMs are specified as members of the class *EmpathyMap*. Each map should be related to a given context through the object property *context* and to a stakeholder through the property *targetStekeholder*. The structure of an EM is defined by specifying the components or sections. Such different elements are sub-concepts of the class *EM_Component* and may be related to a map by using the property *em_component*. In the reference case study considered in this paper, 6 different components have been specified as represented in fig. 2. These components correspond to the sections of the original reference model [Bland, 2012].

Class	Sub-class of	Description
Problem_Context	-	It identifies a given scenario, use case or target study case.
Scenario	-	Equivalent to Problem_Context.
Stakeholder	-	A stakeholder as in a common meaning.
RelevantFact	-	Fact, data or relevant information related to a context.
EmpathyMap	-	EM related associated with a given stakeholder.
EM_Component	-	Component of an EM as in its original structure (Fig. 1).
Hear	EM_Component	"Hear" component as in the EM's original model.
See	EM_Component	"See" component as in the EM's original model.
Pain	EM_Component	"Pain" component as in the EM's original model.
Gain	EM_Component	"Gain" component as in the EM's original model.
SayAndDo	EM_Component	"Say & Do" component as in the EM's original model.
ThinkAndFeel	EM_Component	"Think & Feel" component as in the EM's original model.

Table 1: Main classes

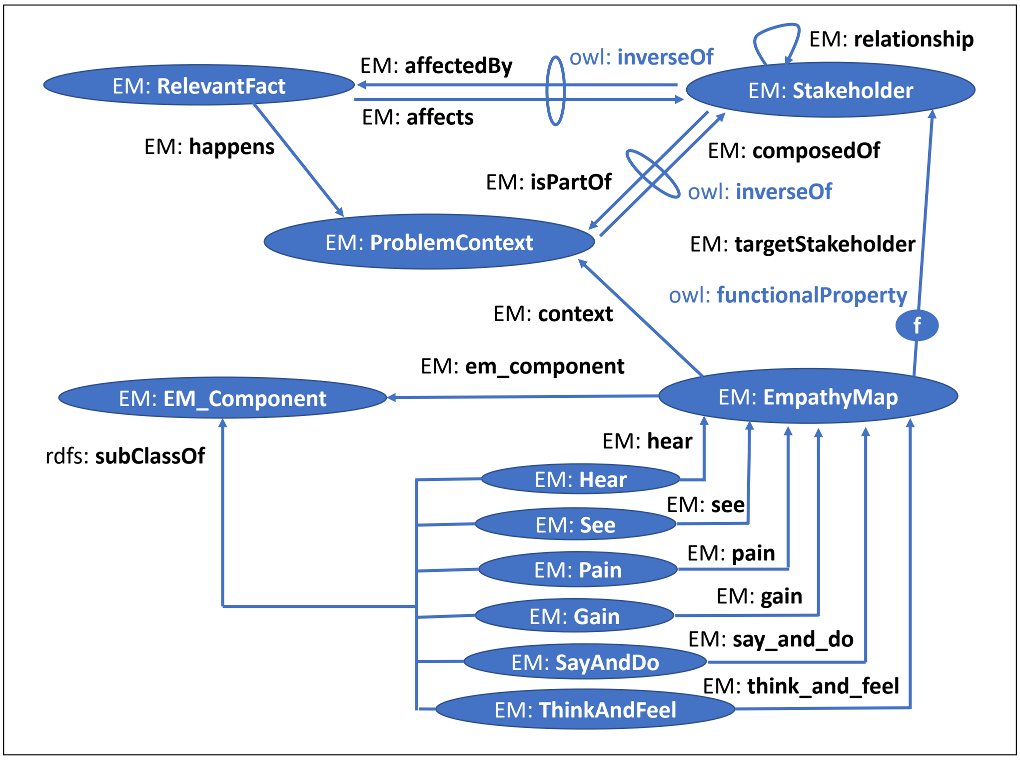


Figure 2: Overview of *EM Ontology*.

Property	**Type**	**Domain**	**Range**	**Description**
composedOf	Object	ProblemContext	Stakeholder	It relates stakeholders to the context.
isPartOf	Object	Stakeholder	ProblemContex	It relates stakeholders to the context.
affectedBy	Object	Stakeholder	RelevantFact	It associated stakeholders with relevant info.
affects	Object	RelevantFact	Stakeholder	It associated stakeholders with relevant info.
happens	Object	RelevantFact	ProblemContext	It relates relevant info to the context.
context	Object	EmpathyMap	ProblemContext	It links an EM to its context.
targetStakeholder	Object	EmpathyMap	Stakeholder	It associated the EM with a stakeholder.
em_component	Object	EmpathyMap	EM_Component	It relates a generic component to its EM.
hear	Object	Hear	EmpathyMap	It relates an "hear" component to its EM.
see	Object	See	EmpathyMap	It relates a "see" component to its EM.
pain	Object	Pain	EmpathyMap	It relates a "pain" component to its EM.
gain	Object	Gain	EmpathyMap	It relates a "gain" component to its EM.
say_and_do	Object	SayAndDo	EmpathyMap	It relates a "say & do" component to its EM.
think_and_feel	Object	ThinkAndFeel	EmpathyMap	It relates a "think & feel" component to its EM.
description	Data	-	-	Generic description for a concept.

Table 2: Main properties

Semantic Enrichment and External Linking Looking at applications in the different contexts and domains, in the most general terms, a significant enhancement identifiable a priori is the capability to semantically enrich (e.g. [Abel et al., 2011] [Angeletou, 2008] [Belsky et al., 2016]) the original conceptual model, as well as to link external data, information and, eventually, knowledge. Indeed, if enabled in the Semantic Web, the proposed data infrastructure provides such a support by creating a descriptive environment in which annotations based on different vocabularies are integrated together. As any content in the Web is uniquely identifiable, the supporting ontology creates a unique point of convergence for the target knowledge system.

Cross-scenario analysis and knowledge re-use At an application level, a semantically enriched and interoperable environment increases the capability in terms of both synthesis and analysis. Indeed, the overall knowledge building process becomes ontology-driven and results in enhanced features from a knowledge re-use and retrieval perspective. In the concrete case object of this study, cross-scenario analysis is fully supported.

3.3 An example of use

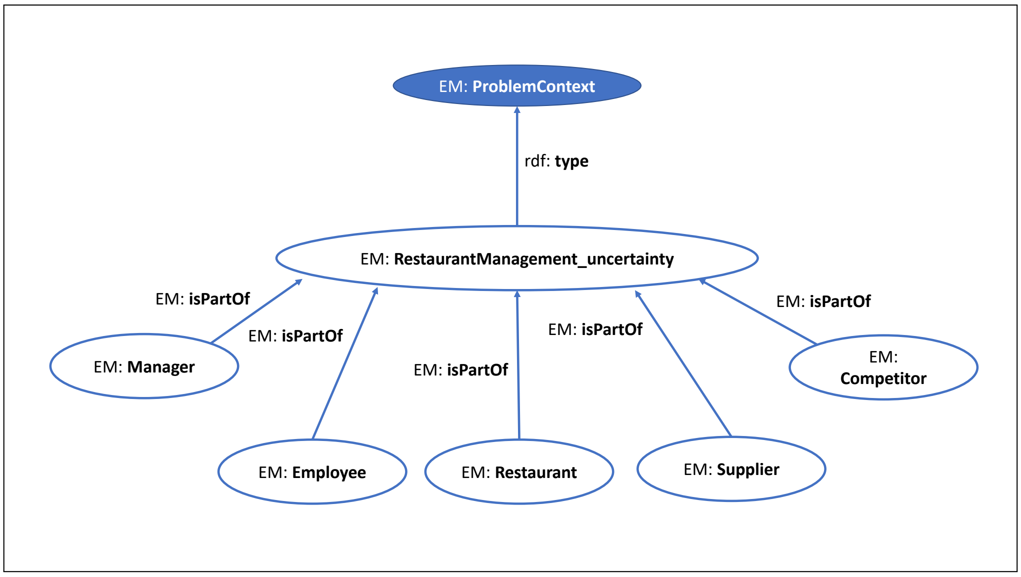
This section provides an example of use of ontology previously described to address a concrete synthetic business case. In order to keep the example as easy and understandable as possible, we propose a very simplified business case related to the management of a restaurant which is facing some challenge due to its very traditional approach to business and everyday operations. Additionally, we describe the main data infrastructure only with a focus on the most relevant aspects. Details (e.g. descriptors, labels and not primary relationships) are not reported.

More concretely, we first address the formal specification of the target scenario both with its characterization, then we describe examples of EMs and, finally, we deal with some relatively complex query examples.

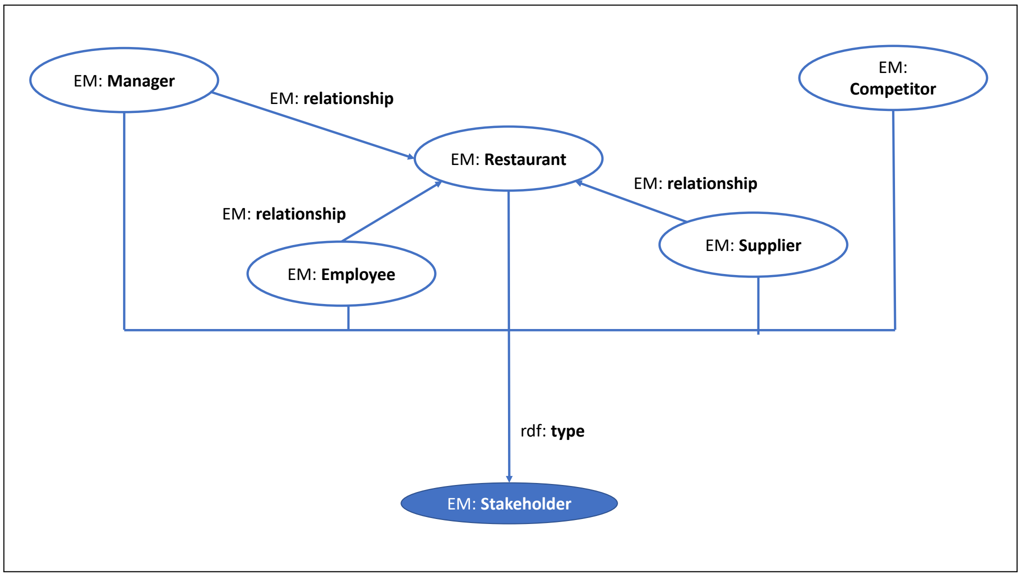
3.3.1 Formal specification of the scenario

Fig. 3 proposes an example of formal specification of a target scenario. Such a definition, visually represented as a knowledge graph, focuses on key concepts and relationships and misses most details.

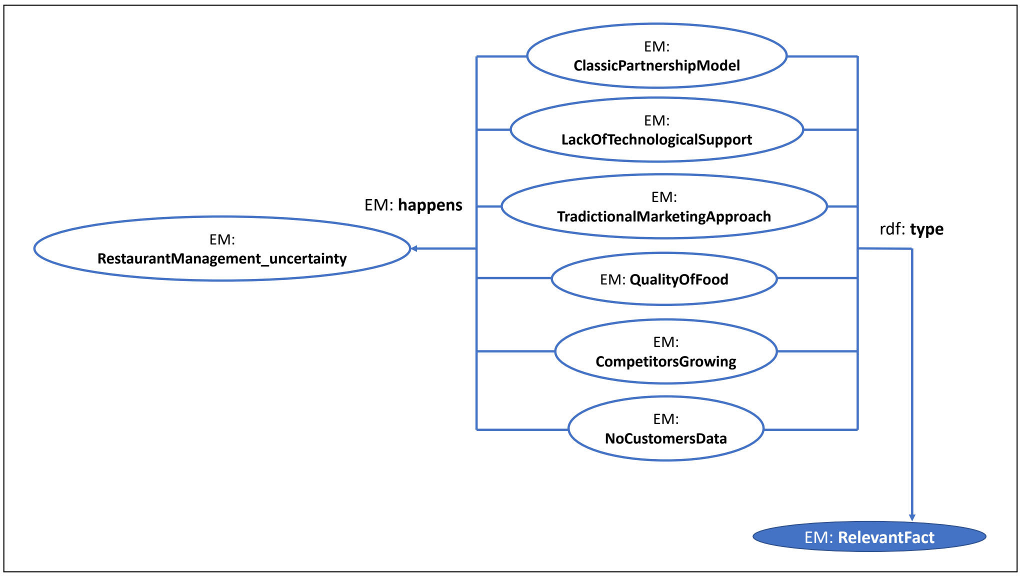
The problem context, *RestaurantManagement_uncertainty*, is defined as an instance of the class *Problem-Context*. As shown in fig. 3a a number of stakeholders (*Manager*, *Employee*, *Restaurant*, *Supplier*, *Competitor*) are associated with the target problem through the property *isPartOf*. Relationships existing among stakeholders are proposed in fig. 3b and are established by using the property *relationship*. Finally, a number of characterizations (instances of the concept class *RelevantFact*) are related to the target scenario (through the property *happens*) to characterize it (fig. 3c).



(a) Problem context and related stakeholders.



(b) Relationship among stakeholders.



(c) Characterization of the target scenario.

Figure 3: Partial specification of a target scenario.

3.3.2 Formal specification of Empathy Maps

The diagram in fig 4 shows the formal definition of two EMs (*Manager_EM* and *Employee_EM*) associated through the property *targetStakeholder* with the manager and the employee respectively. The EMs are also related to the context scenario *RestaurantManagement_uncertainty* by adopting the property *context*.

An informal specification of synthetic EMs is proposed in fig. 5, while their partial formalization by adopting the proposed ontology is represented in fig. 6. As shown, the dynamic use of the vocabulary allows an easy definition for the key data infrastructure that, as previously discussed, can be characterised and semantically enriched depending on the application context.

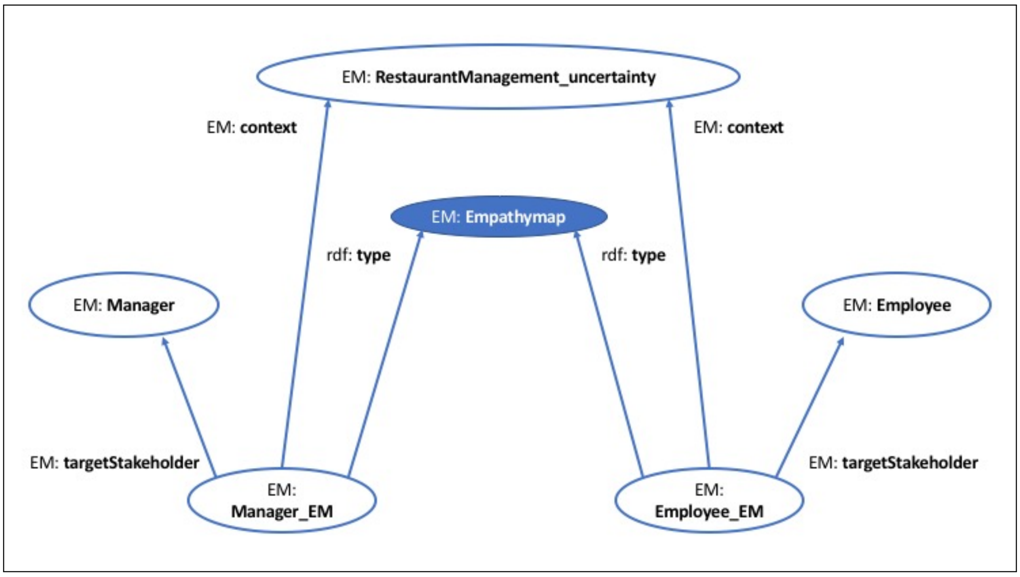


Figure 4: Association of EMs with target stakeholders and scenario.

3.3.3 Complex query

The preferred interaction mode with ontological structure is definitely based on the adoption of rich query languages [Kollia et al., 2011] (e.g. SPARQL [SPA,]). Complex query supports an high level of abstraction as queries may be designed just looking at the main ontological schema.

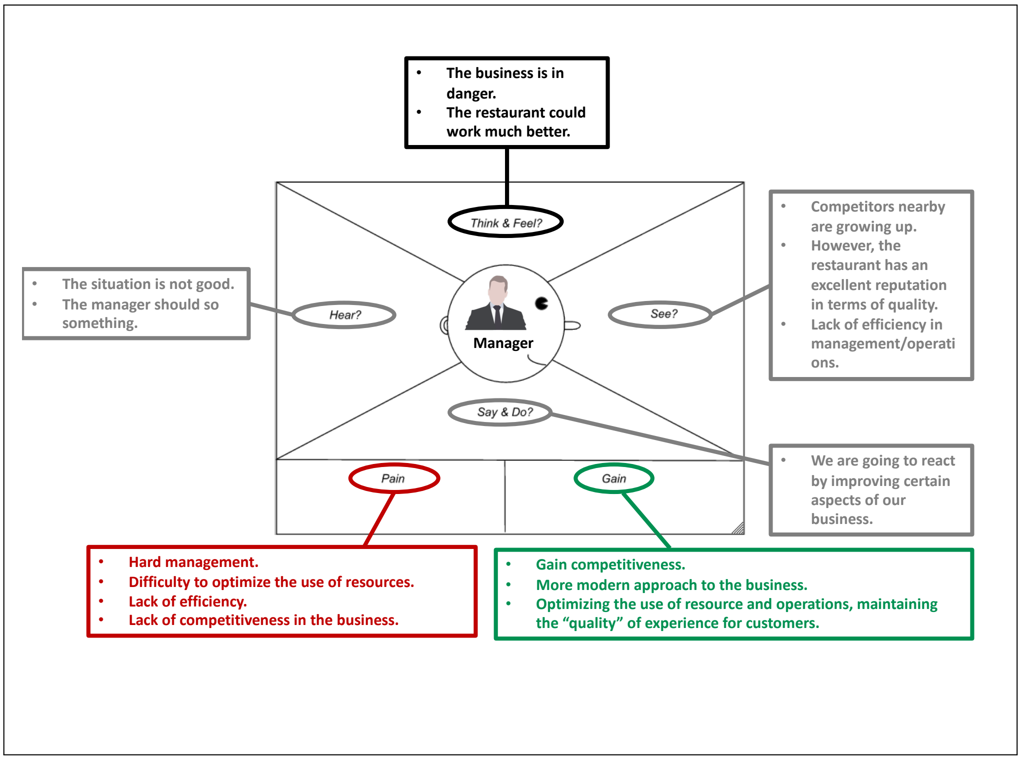
Basic examples of query to support single scenario as well as cross-scenario analysis are reported below. *Q1* retrieves all characterizations of a given scenario; *Q2* retrieves all EMs both with the characterizations associated; finally, *Q3* returns the participation of a given stakeholder X in the different scenarios.

Q1: Retrieving all characterizations of a given scenario S.

```
SELECT  *
WHERE   {
     {S ?y ?x}
      UNION
     {?x ?y S}
   }
```

Q2: Retrieving all EMs and their characterizations.

```
SELECT  *
WHERE   ?x a EM:EmpathyMap.
        ?x ?y ?z
```



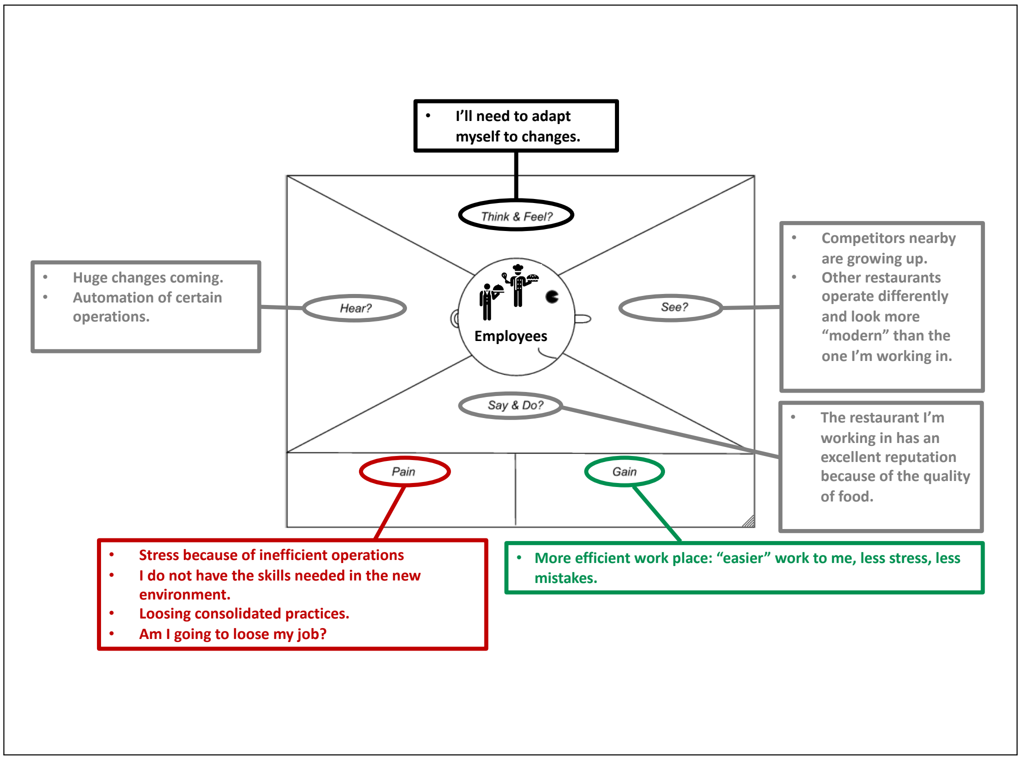


Figure 5: Two EM examples.

Q3: Retrieving the participation of a given stakeholder X in the different scenarios.

```
SELECT  ?scenario
WHERE   X EM:isPartOf ?scenario
```

3.3.4 Visualizations

In terms of visualizations, ontological structures are (or may be) understood like Knowledge Graphs [Pujara et al., 2013]. The Knowledge Graph approach is very valuable as, if properly used, can combine multiple

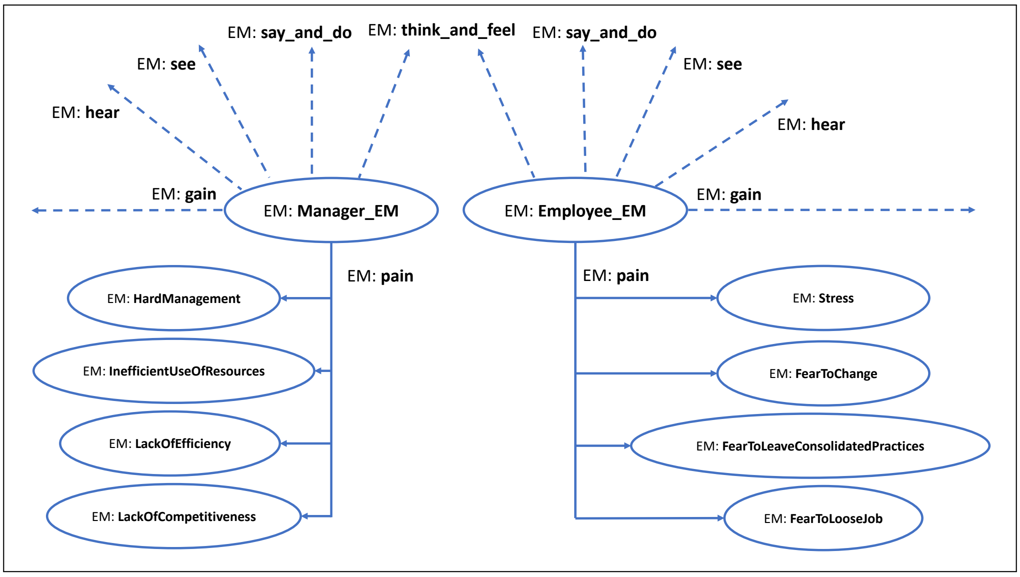


Figure 6: Partial formal specification of EMs.

aspects from different disciplines, including data visualization [Friendly, 2008], data semantics [Madnick and Zhu, 2006] and complex network [Zhu et al., 2018].

The visualization of the example proposed as a Knowledge Graph from our research prototype is proposed in fig. 7a. It focuses on classes and individuals as per OWL specifications [OWL,] but doesn't include attributes to keep the density of the graph relatively low. Our visualization approach adopts filled circles for classes and unfilled circles for individuals (instances). The number of instances belonging to each class is represented and the size of the corresponding representation is proportional to such a number. Additionally, the result of a given query can be visualised over the graph (fig. 7b).

4 Applications

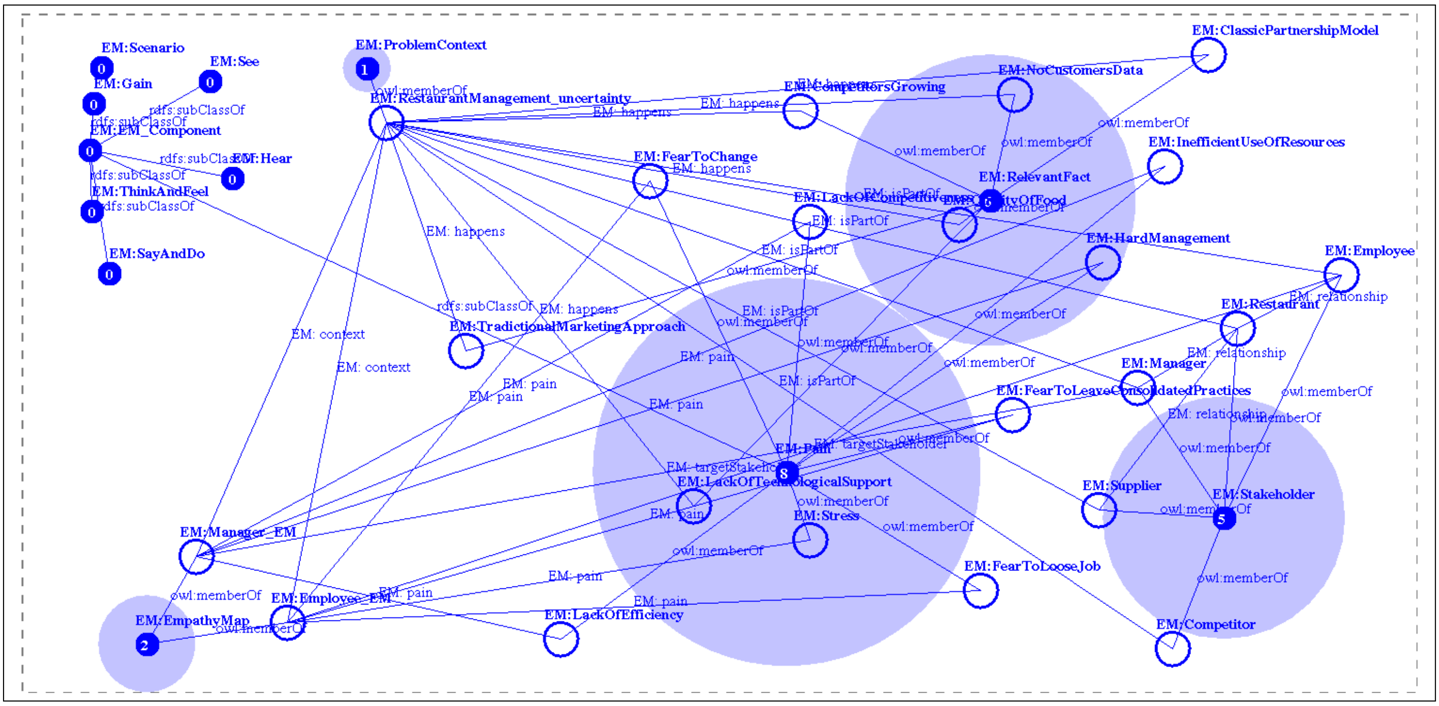
This paper focuses on the definition of a formal specification for EMs in context. Potential applications of such a data structure should mainly fall in the two following categories:

- **Expert systems/tools.** If Design Thinking methodologies need to be supported by computer-based tools, the proposed ontological approach can provide an effective, flexible and interoperable backbone to integrate and enable data, information and knowledge within the Semantic Web. Automatic reasoning, complex query, visualizations and ontology analysis [Guarino, 1995] may facilitate the development of advanced features (e.g. AI-powered).

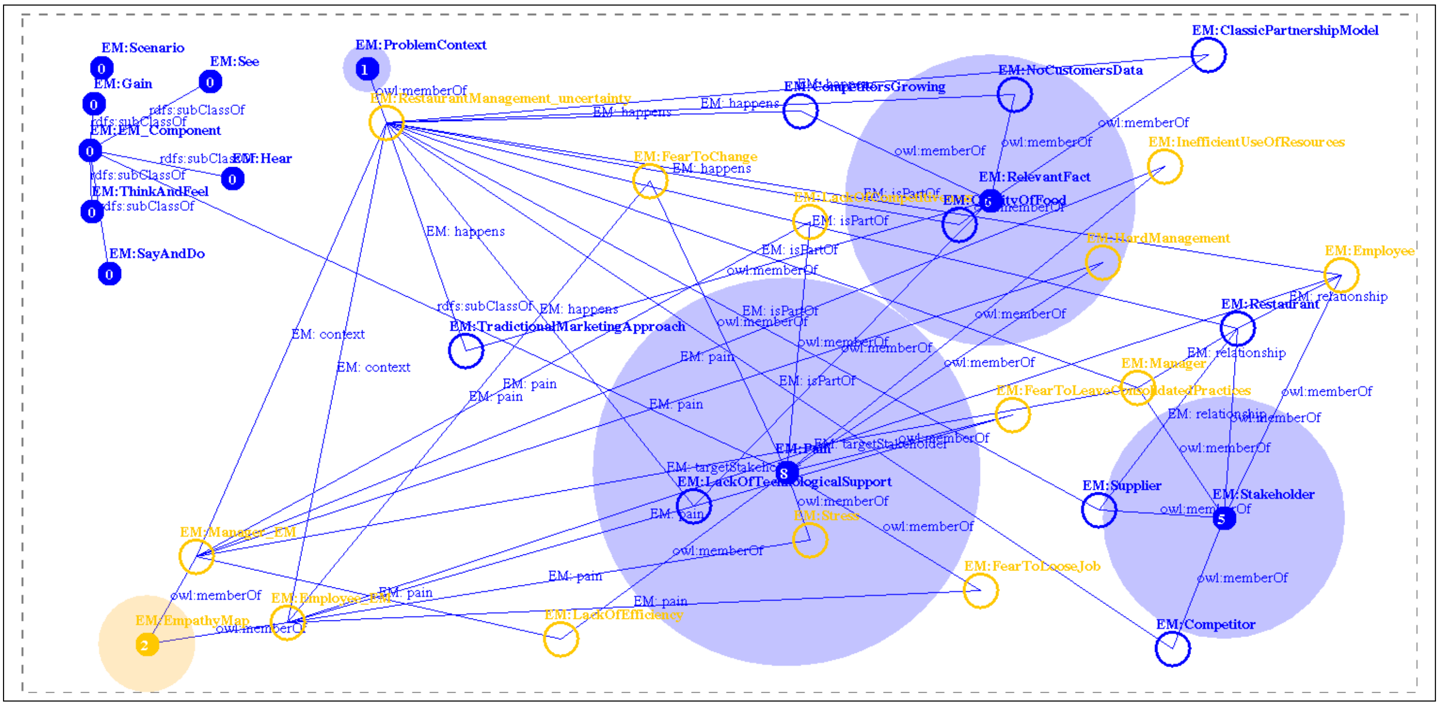
- **Education.** Design Thinking is extensively adopted in education [Koh et al., 2015]. We believe that enabling knowledge re-usability and extended analysis capabilities may further foster creativity. Last but not least, the ontological approach could be functional to novel approach to learning (e.g. Pervasive learning [Thomas, 2005]).

- **Adaptive systems, disruption and non-deal conditions.** The complex and challenging situation we are living with the COVID-19 has quickly converted the adaptation to disruption and to non-ideal conditions a pressing need. At this stage, it is commonly assumed that a further digital support for consolidated methods, processes and practices is a smart move forward in terms of resilience and, definitely, a good direction looking at a sustainable future. Design Thinking is normally a team activity. Online platforms, among others, help teams to work remotely and, in this specific case, the ontological approach could be a determinant asset to an effective development upon sophisticated technology.

- **Multi, Inter, Trans-disciplinary environments; Knowledge sharing and Communication.** Additional challenges arise within environments which present multi, inter or trans-disciplinarity. Indeed, in such evolving domains problems are often approached from multiple perspectives that need to be properly integrated. It implies stronger requirements in terms of formal specification of concepts that also need to be related to already existing concepts from different disciplines. The communication of knowledge at the different levels may be critical, even within consolidated environments. Regardless



(a) Visualization as a Knowledge Graph.



(b) Visualization of query result.

Figure 7: Visualizations as a Knowledge Graph.

of the intent and extent of the Design Thinking process, a significant heterogeneity is expected. The ontological approach proposed can facilitate the effective management and contribute to maximise value creation and knowledge sharing.

Approaching real-world scenarios From a technology perspective, the ontology proposed is developed in OWL and it is directly usable within any system that adopts semantic technology. While specification and query languages have been standardised by W3C[1], the research community has provided a number of valuable assets that assume such standards, including reasoners (e.g. Pellet [Sirin et al., 2007] and Hermit [Glimm et al., 2014]), editors (e.g. Protege [Musen, 2015]), ontology libraries [d'Aquin and Noy, 2012] and triple-store [Rohloff et al., 2007]. The vocabulary provided assumes the 6 components model previously described. It can be extended or customised through ontological features (e.g. equivalent classes, properties, attributes

[1]W3C - https://www.w3.org

or individuals as per OWL specifications) to work with other models that can eventually co-exist and work within a unique knowledge space. As an example, fig. 8 shows in concept the semantic integration of different models characterized by 4 [Gibbons,], 5 [Gibbons,] and 6 components respectively. Intuitively, extensions and customised semantic relationships (equivalence in this specific example) may be defined by adopting OWL mechanisms. An exhaustive discussion of such mechanisms is out of the scope of this paper.

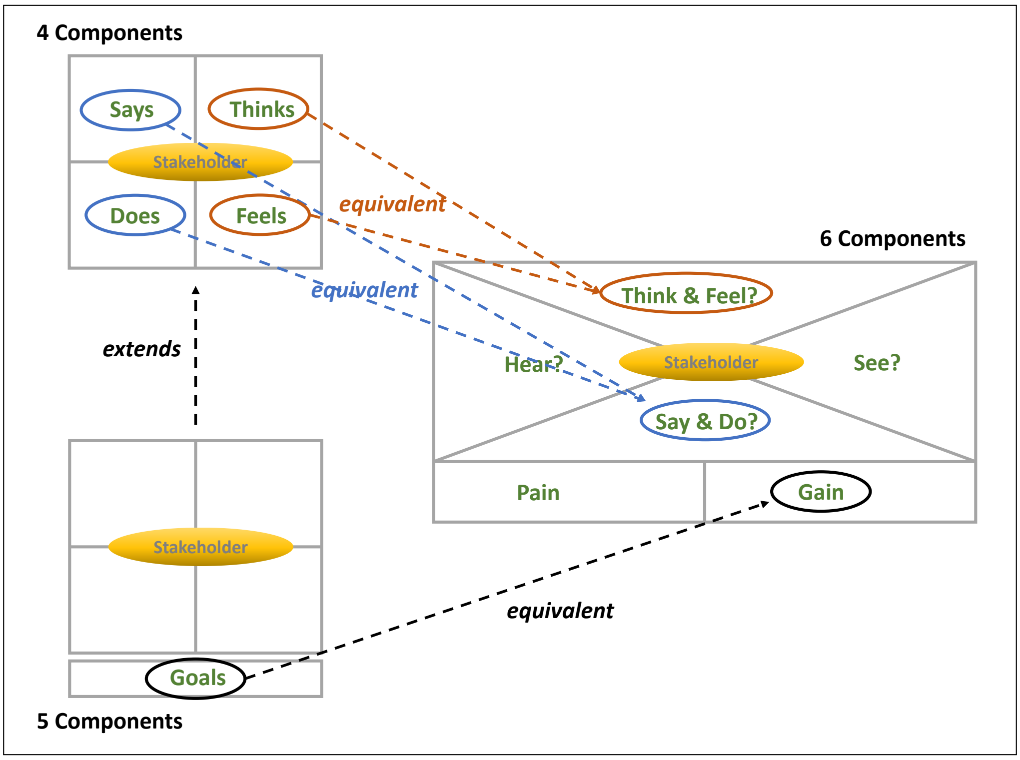


Figure 8: Integration of models characterised by a different number of components.

5 Towards AI-powered tools for Design Thinking

Artificial Intelligence (AI) applications are proliferating and the actual impact on our lives is topic of intense discussion [Makridakis, 2017] along a number of ethical concerns [Russell et al., 2015]. While the relationship between AI and creativity is definitely not a novelty [Boden, 1998], the last generation technology and its unstoppable evolution within a data-intensive society could radically change the current understanding of Design Thinking and, more in general, of system design.

The proposed ontological approach in a fully machine-processable context, which assumes interoperability at a Web - i.e. global - level, intrinsically enables the process within Knowledge-based Systems, which are constantly evolving themselves [Zhang et al., 2017]. In general terms, a rich knowledge-base supported by smart interaction features defines a completely novel scenario in which creativity meets data-centric approaches at a high-level of abstraction.

The specific step addressed in the paper is related to stakeholder analysis by adopting empathy mapping. We believe that such a design step, characterised by a strictly analytical focus, can be especially benefited by the ontological approach which is likely to facilitate the combination of situation-specific and contextual information, as well as it could contribute to minimise biases and differentiate useful from misleading evidence. In other words, while the impact and effect in practice of AI on the whole Design Thinking process is largely to be assessed and can probably considered as application-specific, a restricted emphasis on the analysis step allows much more focused considerations which points towards a more evidence-based and data-driven resulting analysis. However, despite the optimistic interpretation, some risks are easily identifiable a priori as an analysis that relies on a concrete knowledge base could further empower bias, eventually also from the organizational culture [Elsbach and Stigliani, 2018].

Overall, we do expect the ontological approach to make the knowledge resulting from the different sources (e.g. complex Business Analytics) actionable in practice and, in the limit of the possible, to be re-usable in context.

6 Conclusions and Future Work

Focusing on the empathy mapping phase, we have proposed an ontological approach to Design Thinking. As extensively discussed, it enables any system or tool adopting such a philosophy within the Semantic Web. The capabilities in terms of data integration and re-use via interoperability are automatically integrated with a number of advanced tools and techniques (automatic reasoning, complex query, visualization) to support the development of advanced feature within the different application domains.

We believe that the ontological approach can drive and optimally support the application of Design Thinking in the context of the most relevant trends which currently assume or are based on large amount of heterogeneous data. We believe that, under the realistic assumption that any problem is somehow unique or presents anyway unique characteristics, increasing the capabilities in terms of analysis by properly supporting data-driven and evidence-based approaches can further empower the Design Thinking philosophy. The ability to systematically and automatically compare different scenarios or to perform cross-scenario analysis of a given stakeholder are clear examples of added value to system designers.

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