Human-Machine Collective Intelligence for Decision Support: Semantic Interoperability Based on Multi-Aspect Ontologies

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Abstract. Collective intelligence is of a great potential to decision support because often collective decisions are thought more efficient than individual ones. The research views the human-machine collective intelligence as shared intelligence that emerges from the collaboration between humans and software services, their joint efforts and consensus decisions. For multiple collaborators, it is very unlikely that they share a common view on the same domain or problem. Thus, due to the heterogeneous nature of the collaborators, one of the key requirements to enable such a collaboration is providing for semantic interoperability. The paper suggests using ontologies to support semantic interoperability and proposes the apparatus of multi-aspect ontologies thus enabling humans and intelligent software services to self-organize into a collaborative community for decision support. The major ideas behind the approach are demonstrated by an example from the smart city domain.

Keywords. Human-machine collective intelligence, semantic interoperability, multi-aspect ontology, decision support

1. Introduction

Intelligent decision support collecting information related to the current situation analysis and assisting in solving various typical problems becomes essential since otherwise, one can sink in the ocean of the available today information and problems to be solved [1], [2].

Collective intelligence is an emergent property from the synergies among data-information-knowledge, software-hardware, and humans with insight that continually learns from feedback to produce just-in-time knowledge for better decisions than any of these elements acting alone. A collective intelligence system could help organize all these elements to improve decision making [3]. The Decision 2.0 framework shifting to collective decisions in the era of Web 2.0, postulates three general types of approach to accomplish the decision making objectives. They are outreach, additive aggregation, and

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self-organization. The former two types suppose involvement of various sources providing ideas and information. The latter type, self-organization, is mechanisms that enable interactions among community members, which can result in the whole being more than the sum of its parts [4]. That is, self-organization is the mechanism that can help to achieve the main goal of collective intelligence, that is to provide more knowledge than any individual element provides.

In truly intelligent decision making systems the elements above are interoperable only with a shared understanding of the task, the context, and each other's perspectives and capabilities [5]. There are four levels of interoperability [6]: technical, semantic, organizational and legislative. Semantic interoperability is understood as shared semantic interpretation of knowledge presented using meta-models such as Unified Modeling Language (UML [7]) class diagrams and Ontology Web Language (OWL [8]). The problem of shared knowledge faces many obstacles in human-machine environments. Namely, different meanings for terms [9], diverse data formats, diverse ontologies reflecting different contexts and area of practice, diverse classification systems, diverse folksonomies emerging from social tagging in various social media [10], and multiple natural languages [11]. All these obstacles exist when heterogeneous teams aim at providing collective intelligence.

In 2008, T. Gruber addressed the issue of collective intelligence in the Web, where humans and machines contribute actively to the resulting intelligence, each doing what they do best. People are the producers and customers: they are the source of knowledge, and they have real world problems and interests. Machines are the enablers: they store and remember data, search and combine data, and draw mathematical and logical inferences [9]. The Semantic Web was supposed the technology enabling to provide interoperability between humans and machines by utilizing ontologies.

Most of the research on the human-machines activities use multiple ontologies as a mechanism enabling interoperability. Each ontology is a domain representation reflecting specifics of a particular problem this ontology was built for. The terminologies and formalisms depend on the tools used for efficient solving domains' tasks. The difficulty of supporting conciliated ontologies that capture different aspects of the same domain, as well as developing an ontology model for representation and processing of information used for solving problems of different nature, lies in the necessity to operate not only with different terminologies but also with different formalisms used to describe different aspects. The problem of heterogeneity can be overcome through having multiple aspects within a common multi-aspect ontology. The multi-aspect ontology is defined as an ontology that specifies different interrelated aspects (facets, constituents, perspectives) of a complex problem domain. On the one hand, the multi-aspect ontology provides for the common vocabulary enabling the interoperability between different decision-making processes and ontologies supporting these, and, on the other hand, it makes it possible to preserve internal notations and formalisms suitable for efficient support of these processes.

This paper addresses the problem of semantic interoperability support in human-machine collective intelligence systems through application of a multi-aspect ontology. The main research contribution is a methodology for the above ontology development. The methodology has been validated through the development of a multi-aspect ontology for a human-machine collective intelligence decision support system in the smart city domain.

The paper is structured as follows. Section 2 presents a review of related research. The developed methodology is described in Section 3. It is followed by an example of the developed multi-aspect ontology. Main results are summarized in the Conclusion.

2. State-of-the-Art

The Section outlines various approaches to develop ontologies representing different knowledge perspectives. The most suitable ones are considered in detail and analysed.

Ontologies support the formalization of rational and intuitive decision behavior in the Pi-Mind technology [12]. This technology offers a compromise between human-driven decision-making and machine-driven decision-making with regard to Industry 4.0. Pi-Mind captures the best humans' decision models using the parametric approach to decision-making complemented by the functional approach. The parametric approach is responsible for rational behavior. It is used to value a personalized set of preferences defined for a set of possible situations in the form of parameters for a particular human expert. The functional approach is purposed to take into account subjectivity in the decision-making. Using this approach a unique freedom map is built based on integration of factors of different origins influencing the expert's ideas about the freedom of actions in different situations. Based on the expert's values and the set of decision-making schemes used for specific tasks, a persons' decision system is built. Such systems are kept by Pi-Mind robots. As a result, the robots become able to make decisions in analogous situations without any human accompany. The formalization of the rational and intuitive human behaviour uses semantic modelling and it is based on three kinds of ontologies: upper ontology providing basic means for describing decisions and decision-making; Pi-Mind specific ontology, describing a value based model of decision-making; and domain ontologies describing the structure of decision scenarios for specific domains.

In the automating design domain relying upon the human–machine integrated automating design paradigm, ontologies are used to support interoperability between machines, and between machines and humans. Different approaches aiming at modelling the automatic design knowledge represent different aspects of design in their ontologies. Examples of such aspects are process, function, physical product and issue [13]; requirement ontology, product finish ontology and machine motion ontology [14]. The most recent approach [15] distinguishes two aspects: the design ontology to describe the product and the design process, and the resource ontology to provide an integrated representation of human knowledge and computer knowledge for automating design.

The authors of a model-driven interoperability framework for technical support of co-evolution strategy of products and manufacturing systems [16] address the interoperability problem by connecting ontologies through establishing "connector framework" matching these. This framework connects ontology subclasses representing product modules, manufacturing alternatives, and operations. Interoperability between the product life management tool and the production capability tools is supported by the ontologies, that are queried for assessment of the plant capabilities.

Ontology matching [17] seems to be one of the solutions to the interoperability problem. But in reality, automatic ontology matching is still not reliable enough while manual ontology matching takes too much efforts and time. There exist some works aimed at the improvement of ontology matching through enriching ontologies with additional information (e.g., extension of DAML+OIL for description of configuration problems [18], introduction of semantic annotations [19], etc.), but they are not enough to solve the problem of integrating heterogeneous information and knowledge described in different ontologies.

Lim, Liu, and Lee [20] suggested a solution based on semantically annotated multi-faceted ontology for a family of products that can automatically identify semantically-related annotations. This work has helped to identify the further direction of the present research aimed at integration of heterogeneous knowledge through developing a single complex multi-aspect ontology.

Two main and most promising approaches can be distinguished among the studies on multiple domain representations using ontologies. They are multilingual ontology [21] and granular ontologies [22].

The goal of multilingual ontologies is to resolve terminological issues that arise due to usage of different natural languages. Such ontologies are built as an ontology comprising language-specific fragments with relationships between terms and it might be a straightforward enough solution for multi-aspect ontology. However, a multilingual ontology is formulated in a single formalism and collecting together, for example, knowledge about motivation strategies (described via production rules) and about structure of the problem under consideration (described via a hierarchy) can lead to losing certain semantics due to the necessity of formalism transformations. As a result, this approach cannot solve the problem formulated.

Granular ontologies rely on the integration of ontology-based knowledge representation with the concept of granular computing. Granular computing is around the notion of granule that links together similar regarding to a chosen criteria objects or entities ("drawn together by indistinguishability, similarity, proximity or functionality"). The granules can also be linked together into bigger granules forming multiple levels of granularity. Granular ontologies seem to be a suitable solution to support multiple aspects: they enable splitting the knowledge in smaller areas with consistent terminology and formalisms. The possibility to form a hierarchy (generalisation) is also beneficial due to the possibility to define generic concepts and relationships at higher levels. However, different decision support processes often overlap in terms of used information and knowledge (Figure 1). This means that there exist multiple processes that assume usage of the same information and knowledge. Granular ontologies do not solve the problem of terms having different meaning in different processes.

3. Methodology

An analysis [23] of various ontology development methodologies allows ones to distinguish 5 general steps in this process: 1) identification of the purpose and scope of the ontology; 2) identification of concepts and relationships, and terms to name these concepts and relationships; 3) ontology engineering; 4) ontology verification; 5) ontology validation. These steps serve as the guide to develop the multi-aspect ontology for interoperability support in human-machine collective intelligence systems.

Development of the multi-aspect ontology follows the proposed here methodology. At first, the interoperability requirements are defined for identification of the purpose and scope of the ontology. Then, the aspects of the ontology are specified based on the information acquired at the first step and its logical continuation. Next, ontologies for each of the aspects are developed. These aspects are integrated and “global level” is formed out of the concepts that are considered to be common for the most of aspects. The steps of verification and validation finalize the ontology development.

3.1. Interoperability Requirements Definition

At this step, the information requirements for interoperability between the collective intelligence community members with the purpose of self-organization to provide for decision support are defined. This step is responsible for definition of

- Who will use and maintain the ontology?
- What knowledge the ontology will cover?
- What are the purposes of the ontology?

The answers to these questions may change during the ontology development process, but at any given time they help to limit the scope of the model. Below, this step is described with regard to interoperability within a community providing collective intelligence for decision support.

Generally, the community providing collective intelligence is considered comprising humans and software resources. The requirements for interoperability between the community members include requirements common for both kinds of members and requirements having special importance for humans.

Common requirements for interoperability in decision support systems:

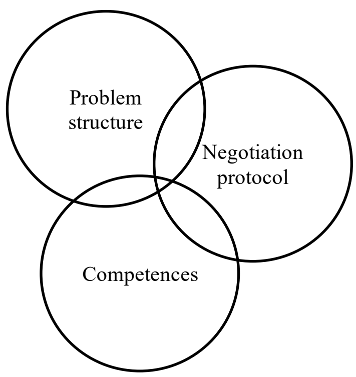

Figure 1. Example of overlapping decision support processes

- Motivation to participate in decision support. Motivation is a precondition of success of the collaboration. Moreover, the motivation influences decision-making process.
- Clarity of the problem. The decision support problem must be clearly represented. The representation must give to the community members clear understanding of what they are expected to do in the current situation (to provide information, to choose an alternative, to perform some computations, to do some activities, etc.) As well, the information based on that decisions are made must be understandable for the members. That is, data, alternatives, constraints, preferences, etc. must be explicitly represented.
- Competencies accounting. The competencies of the community members must be taken into account to ensure appropriate decisions.
- Negotiation patterns. In complex systems with heterogeneous members, negotiation patterns facilitate information/knowledge exchange and especially useful to organize information/knowledge exchange between humans and machines.

Requirements specific for humans in human-machine collective systems:

- Representations for the problem and accompanying information must be human-readable.
- Machines are expected to provide support for complex (e.g., computational) tasks. They are supposed to self-organize for human support.

3.2. Aspect Definition

At this step, the aspects of self-organization for decision support are defined. This step is based on the information acquired at the first step and is its logical continuation. The following questions are answered:

- Which subproblems of the collective intelligence community self-organization are to be solved with the help of the ontology being developed?
- Which of the subproblems can be solved separately, and which are inseparable?
- Which formalisms are usually used for solving identified subproblems?

As a result, identified subproblems form aspects of the future multi-aspect ontology, with inseparable ones being integrated in one aspect, and others (especially those, that use different knowledge models) are into separate ones. Aspect definition for the multi-aspect ontology for self-organization of a collective intelligence community to provide for decision support is presented below.

Two-types of aspects are distinguished: basic and specific. The basic aspects are usually task-independent. They represent concepts and relationships needed to organize a community supporting decisions in any domain. The specific aspects are always task-dependent and make the community task-oriented.

The set of basic aspects comprises Motivation, Problem, Competency, and Negotiation protocol (Figure 2).

Motivation is the reason for participation in the decision support activity. Results obtained in the research on modelling the motivation domain in Enterprise Architecture [24] and on development of ontologies to represent human emotional, cognitive, and motivational processes [25] can provide some ideas of what concepts and relationships can be used to represent Motivation.

Competency is a quality made up of skill and knowledge needed to successfully complete a task. An example of such an ontology is an ontology for skill and competency management [26].

Problem is the decision support problem to be solved in the current context. The problem concept is used to represent conventional decision support problems (situation awareness, problem identification, development of alternatives, choice of a preferred alternative, and decision implementation) and the problem of community self-organization. As well, this concept include domain-specific tasks, i.e. the user tasks for which the community provides support.

Negotiation protocol is a set of rules for communication of negotiating parties towards achievement of a desired final outcome. A great effort on development of an ontology for automated negotiation in open environments [27] provides different aspects of such a protocol. This effort can be used to model the concept of negotiation protocol.

The category of specific aspects is represented by two concepts Input/Output and Task. The concept Task represents the user task and the tasks related to it. For instance, this concept is used for representation of subtasks when the user task is decomposed. Input/Output is intended to represent data and information used at different stages of a decision support process (context, alternatives, criteria, preferences, constraints, etc.).

3.3. Development of Aspect Ontologies

At this step ontologies for each of the aspects are developed. This can be done based on any ontology development methodology (e.g., METHONTOLOGY [28]) since the aspects are generally independent. Obviously, the ontology reuse is beneficial for more or less typical subproblems that have already been paid significant attention form the research community (e.g., negotiation protocol ontology), however, development of ontologies from scratch is also possible if no appropriate existing ontologies are found. Aspect ontologies are proposed to be reused and further developed. Here, the issue of development of these ontologies is not considered. Some ideas of sources ontologies are discussed in the Section above.

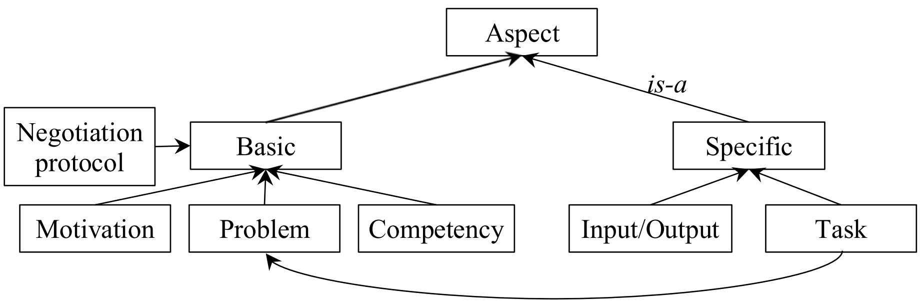

Figure 2. Ontology aspects

3.4. Aspect Integration

At this step, the aspects are analyzed with regard to common concepts that need to be identified and often taken to the common part of the multi-aspect ontology. It is useful to write down a list of all such concepts and then to form a "global level" out of these. After that, these terms are associated with those in the aspects. Besides, horizontal relationships should also be defined at this step for classes that are common for two or more aspects, but which are not high-level enough to be taken into the global level. This step is partially described in Section 4.

3.5. Verification

The goal of this step is to ensure the internal consistency of the developed global level as well as internal consistencies of the separate aspects taking into account their relations to other aspects. The step of ontology verification involves special techniques and is out of the paper scope.

3.6. Validation

Validation usually takes place during the usage of the developed multi-aspect ontology in a real-life or modeled environment. The accumulated issues are collected, analyzed, and the corresponding modifications are introduced into the ontology. Currently, this step is going on and its results will be available upon completion of this activity.

4. Case Study for Smart City

New information technologies enable various new possibilities enhancing our lives. One of products of this development is appearance of the notion of "smart city" [29]. There is no common definition of this notion, however, its common understanding is a coherent urban development methodology heavily relying on information and communication technologies to gather necessary input and provide information for decision making.

Several representation formalisms for multi-aspect ontologies have been analysed. The most progress in this direction is achieved by M. Hemam who in co-authorship with Z. Boufaïda proposed in 2011 a language for description of multi-viewpoint ontologies - MVP-OWL [30] extended in 2018 with probability support [31].

In accordance with this notation, the OWL-DL language was extended in the following way (only some of the extensions are listed here; for the complete reference, please, see [30]). First, the viewpoints were introduced (in the current research they correspond to ontology aspects). Classes and properties were split into global (observed from two or several viewpoints) and local (observed only from one viewpoint). Individuals could only be local, however, taking into account the possibility of multi-instantiation, they could be described in several viewpoints and at the global level simultaneously. Also, four types of bridge rules were introduced that enable links or "communication channels" between viewpoints (only the bidirectional inclusion bridge rule stating that two concepts under different viewpoints are equal is used in the example below, indicated with the symbol $\overset{\equiv}{\leftrightarrow}$).

The presented below ontology is based on integration of several existing ontologies. Due to the space restrictions, only three aspects are considered to illustrate the developed multi-aspect ontology (Figure 3): "*Competences*", "*Negotiation Protocol*", "*User Task*" corresponding to different processes of the decision support based on human-machine collective intelligence. The three aspects are aimed at different tasks and, as a result, they use different formalisms (below, these are described with the most illustrative concepts).

The task considered in the *Negotiation Protocol* aspect is providing agents with ability to communicate and reach the desired result. Inference rules are defined on top of the negotiation ontology to guide agents' reasoning ability. The negotiation protocol aspect makes agents' negotiation behaviors more adaptive to various negotiation environments utilizing corresponding negotiation knowledge, that does not need to be hard-coded in agents, but it is represented by an ontology [32], [33]. The formalism used in this aspect is OWL, and the example classes are "*Community Member*", "*Human*" (subclass of *Community Member*), "*Agent*" (subclass of *Community Member*), "*Strategy*", "*Utility Function*", "*Parameter*" and "*Role*" (all four are associated with the class *Community Member*).

The *User Task* aspect (category Task in Section 3) is aimed at definition of the user tasks in the considered domain (in the given case study the domain is the smart city user information support), their interdependencies and subtasks, as well as functional dependencies between their parameters. The formalism of object-oriented constraint networks makes it possible to define functional dependencies (represented by constraints) between different parameters of the smart city environment then process these via a constraint solver when a particular situation takes place. As a result, the internal representation is basically consists of entities, their parameters and constraints defined between them. However, for the interoperability reasons, the following connecting classes are defined at the aspect level: "*Entity*", "*Social*" (subclass of *Entity*), "*Physical*" (subclass of *Entity*), "*Cyber*" (subclass of *Entity*), "*Parameter*", "*Domain*", subclasses of the *Domain* class (e.g., "*Healthcare*", "*Education*", etc.), "*Rule*".

The third example aspect is *Competences* where competences of the members of the human-machine community. The competences are organized into a hierarchy for facilitating tasks of matching between competences and tasks to be solved. The following classes are considered in this aspect: "*Community member*", "*Competence*", "*Domain*", "*Competence Level*", "*Competence Statement*" (a more detailed description of this ontology can be found in [34]). In this aspect, an OWL ontology is used.

In accordance with [30] the following ontology elements have been defined:

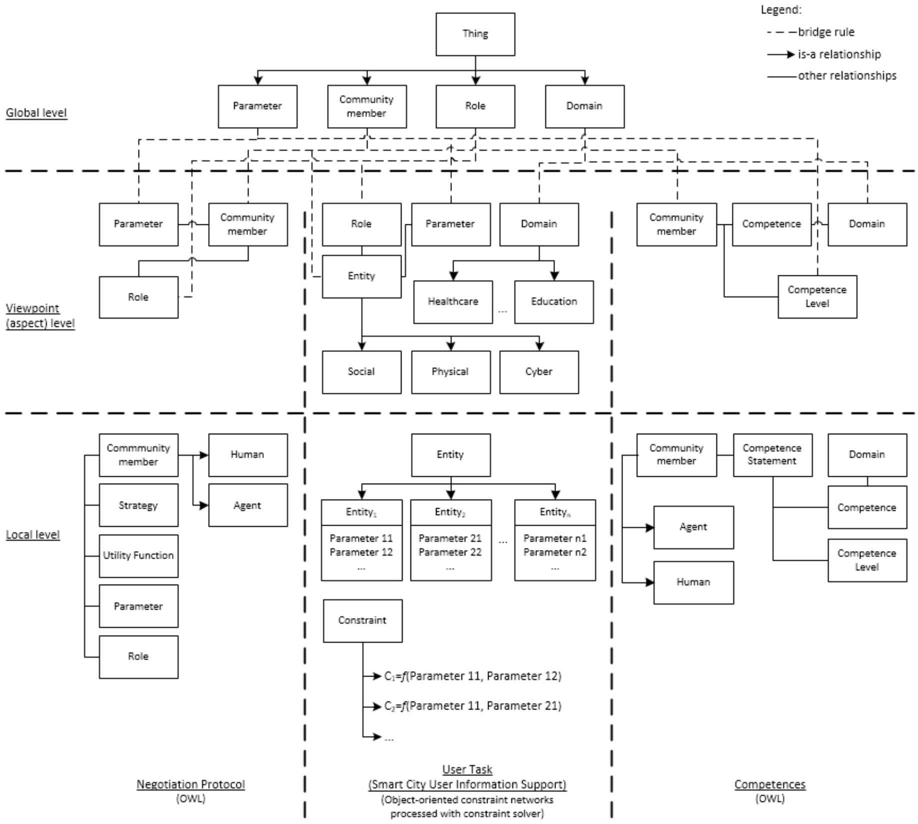

Figure 3. Multi-aspect ontology for three aspects

Aspects (viewpoints): *Competences*, *Negotiation Protocol*, *User Task.*
Global classes: *Thing*, *Parameter, Community Member, Role, Domain.*
Local Classes:

Negotiation Protocol: Human, *Agent*, *Strategy*, *Utility Function*
User Task: Entity, *Social*, *Physical*, *Cyber*, *Rule*, *Healthcare*, *Education*, etc.
Competences: Competence, *Competence Level*, *Competence Statement*

Bridge Rules:

$Parameter \overset{\equiv}{\leftrightarrow} Parameter_{NegotiationProtocol}$
$Parameter \overset{\equiv}{\leftrightarrow} Parameter_{UserTask}$
$Parameter \overset{\equiv}{\leftrightarrow} CompetenceLevel_{Competences}$
$CommunityMember \overset{\equiv}{\leftrightarrow} CommunityMember_{NegotiationProtocol}$
$CommunityMember \overset{\equiv}{\leftrightarrow} Entity_{UserTask}$
$CommunityMember \overset{\equiv}{\leftrightarrow} CommunityMember_{Competences}$
$Role \overset{\equiv}{\leftrightarrow} Role_{NegotiationProtocol}$
$Role \overset{\equiv}{\leftrightarrow} Role_{UserTask}$
$Domain \overset{\equiv}{\leftrightarrow} Domain_{UserTask}$
$Domain \overset{\equiv}{\leftrightarrow} Domain_{Competences}$

i.e., the *Roles* from different aspects are the same roles, and *Entity* from the *User Task* aspect is *Community Member* from the *Negotiation Protocol* aspect.

When the aspects and bridge rules are defined, one can use any required formalism inside each of the aspects. Besides, the existing models can be integrated into such a multi-aspect ontology without significant modification.

5. Conclusion and Future Work

The paper suggests a methodology for building multi-aspect ontologies for interoperability support in a collective intelligence community aimed for decision support. The main problem is that in such a complex domain there are different aspects that have to be maintained simultaneously. Building a multi-domain segmented ontology basically consisting of a number of ontologies (sub-ontologies) can be based on using unchanged source ontologies and the overall structure of such an ontology would be simple and easy to process. However, this would lead to the necessity of continuous translation of information and knowledge between different representations and standards, which is not an easy task. The dynamic structure of the terminology would make this issue even more complex for solving. As a result, this solution was not accepted. Multilingual ontologies can solve the problem of heterogeneity of information and knowledge but lack the possibility to support multiple problem-specific formalisms. As a result it was decided to apply the apparatus of multi-aspect ontologies that do not only enables integration of different aspects but also preserves their internal notations and formalisms.

The suggested methodology consists of six steps: interoperability requirements definition, aspect definition, development of aspect ontologies, aspect integration, verification, and validation. Steps 1, 2, and 4 are illustrated with an example from the smart city domain.

At the current stage of the research, the developed methodology has proved its eligibility to building multi-aspect ontologies supporting interoperability in collective intelligence communities. However, the “validation” step is currently going on and its results will be available upon completion of this activity. After that an analysis of the strong points and weaknesses of the developed methodology and multi-aspect ontology for interoperability support in a collective intelligence community will be performed.

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