Multi-aspect Ontology for Interoperability in Human-machine Collective Intelligence Systems for Decision Support

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Abstract: A collective intelligence system could significantly help to improve decision making. Its advantage is that often collective decisions can be more efficient than individual ones. The paper considers the human-machine collective intelligence as shared intelligence, which is a product of the collaboration between humans and software services, their joint efforts and conformed decisions. Usually, multiple collaborators do not share a common view on the domain or problem they are working on. The paper assumes usage of multi-aspect ontologies to overcome the problem of different views thus enabling humans and intelligent software services to self-organize into a collaborative community for decision support. A methodology for development of the above multi-aspect ontologies is proposed. The major ideas behind the approach are demonstrated by an example from the smart city domain.

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1 INTRODUCTION

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 (Glenn 2013). 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 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 (Bonabeau 2009). 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 (van den Bosch and Bronkhorst 2018). There are four levels of interoperability (European Commission 2017): technical, semantic, organizational and legislative. Semantic interoperability is understood as shared semantic interpretation of knowledge presented using meta-models. The problem of shared knowledge faces many obstacles in human-machine environments. Namely, different meanings for terms (Gruber 2008), 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 (Halpin, Robu and Shepherd 2007), and multiple natural languages (Lévy 2010). All these obstacles exist when heterogeneous teams are aiming at providing collective intelligence.

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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 (Gruber 2008). 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. Difficulties lie in the necessity to operate not only with different terminologies but also with different formalisms used to describe different views. The terminologies and formalisms, in turn, depend on the tools used for efficient solving domains' tasks. The problem of heterogeneity of these ontologies can be addressed 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. The multi-aspect ontology provides for the common vocabulary enabling the interoperability between different decision-making processes and ontologies supporting these, and 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 multi-aspect ontologies. The main research contribution is a methodology for the above ontology development. 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 the example of the ontology developed for the smart city domain. 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 behaviour in the Pi-Mind technology (Terziyan, Gryshko and Golovianko 2018). 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 and embeds them into decision making processes of machines. As a result, the machines become able to make decisions without any human accompany in situations that are similar to the situations for which humans' decision models have been captured. The technology relies upon 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 where intelligent human–machine interaction is supposed, 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 (Ahmed, Kim and Wallace 2005); requirement ontology, product finish ontology and machine motion ontology (Darlington and Culley 2008). The most recent approach (Yin et al. 2015) 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 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 (Lafleur et al. 2016) 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 (Smirnov and Shilov 2013) 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.

Two main and most promising approaches can be distinguished among the studies on multiple domain representations using ontologies. They are multilingual ontology (Espinoza, Montiel-Ponsoda and Gómez-Pérez 2009) and granular ontologies (Calegari and Ciucci 2010).

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. However, a multilingual ontology is formulated in a single formalism and collecting together, for example, knowledge about motivation strategies and about structure of the problem under consideration would not be possible without losing certain semantics.

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. However, different decision support processes often overlap in terms of used information and knowledge. This means that there exist multiple processes that assume collaboration and usage of the same information and knowledge. Granular ontologies cannot solve the problem of terms having different meaning in different processes.

3 MULTI-ASPECT ONTOLOGY BUILDING

An analysis (Fernández-López and Gómez-Pérez 2002) 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.

The multi-aspect ontology is proposed to comprise three levels: local, aspect, and global. The local level represents concepts and relationships observed only from one view. Each aspect can be represented by specific formalism. The aspect level represents concepts and relationships from local level that are shared by two or more aspects. This level provides a uniform shared ontology representation. The global level is the common part of the multi-aspect ontology represented using the representation provided by the aspect level. The concepts represented at this level are associated with those in the aspects.

Development of the multi-aspect ontology follows the proposed here methodology. At first, the purpose and scope of the ontology are identified. Then, the aspects of the ontology are defined 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 Identification of the Purpose and Scope

The purpose of the ontology is determined by the research problem, i.e., support of interoperability in human-machine collective intelligence systems intended for decision support.

The ontology scope is identified based on the information requirements specified with regard to the ontology purpose. They include requirements common for both humans and machines and requirements having special importance for humans.

Common requirements for interoperability:

- 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.
- Competences accounting. The competences 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 such exchange between humans and machines.

Requirements important for humans:

- Representations for the problem and associated 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 Aspects Definition

The ontology scope is the source for aspects definition. The set of questions has been formulated to distinguish these aspects:

- Which subproblems of the self-organization of a community providing collective intelligence 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 multi-aspect ontology, with inseparable ones being integrated in one aspect, and others (especially those, that use different knowledge models) into separate ones.

The present research distinguishes two types of aspects in the multi-aspect ontology supporting interoperability in human-machine collective intelligence systems intended for decision support. They are 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, Competence, and Negotiation protocol (Figure 1).

Motivation is the reason for participation in the decision support activity.

Competence is a quality made up of skill and knowledge needed to successfully complete a task.

Negotiation protocol is a set of rules for communication of negotiating parties towards achievement of a desired final outcome.

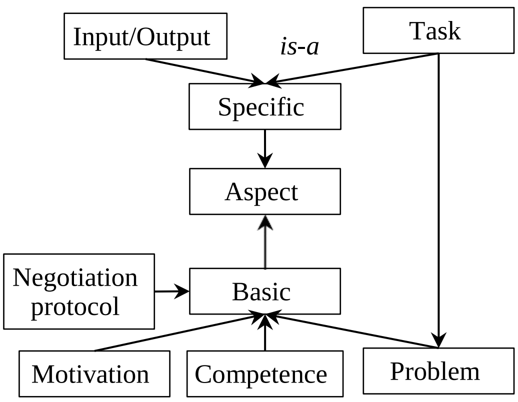

Figure 1: Ontology aspects.

Problem is the decision support problem to be solved in the current context. The corresponding 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. Besides, this concept include domain-specific tasks, i.e. the user tasks for which the community provides support.

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 aspect are developed. This can be done based on any ontology development methodology since the aspects are generally independent (i.e., they can be implemented using different formalisms and representation languages). 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. Although, here, the issue of development of these ontologies is not considered, some thoughts which ontologies can be reused to form the aspects described in the previous Section are provided for.

Results obtained in the research on modelling the motivation domain in Enterprise Architecture (Azevedo et al. 2011) and on development of ontologies to represent human emotional, cognitive, and motivational processes (López-Gil, Gil and García 2016) can give some ideas of what concepts and relationships can be used to represent Motivation.

Sources for an ontology to model Competences can be found in the competence management domain. Examples of such sources are the ontology for skill and competence management (Fazel-Zarandi and Fox 2012), the competence model (Miranda et al. 2017), the competence ontology (Brandmeier et al. 2017), etc.

There are several efforts on development of ontologies supporting negotiations. An ontology for automated negotiation in open environments (Tamma et al. 2002) and its future application to e-commerce (Tamma et al. 2005) provides different aspects of negotiation protocol. The negotiation ontology (Wang, Wong and Wang 2013) supports an ontology based approach to organize the multi-agent assisted supply chain negotiations. The mentioned efforts as well as some others can be used to model the concept of negotiation protocol.

The concepts of Task and Input/Output are domain specific and out of the research scope.

3.4 Aspect Integration

At this step, the aspects are analysed 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 concepts that are common for two or more aspects, but which are not high-level enough to be taken into the global level. A common formalism to represent the common concepts and the horizontal relationships is defined. 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

New information technologies enable various new possibilities enhancing our lives. One of products of this development is appearance of the notion of "smart city" (Dustdar, Nastić and Šćekić 2017). 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. 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 (Anagnostopoulos et al. 2007; Gallacher et al. 2014). Thus, the ontology purpose is defined as support of interoperability in human-machine collective intelligence systems intended for decision support in the smart city domain.

The scope and aspects do not depend on a particular domain and are as described in Section 3.

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 (Hemam and Boufaïda 2011) extended in 2018 with probability support (Hemam 2018). 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 (Hemam and Boufaïda 2011)). 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 2): *Competences*, *Negotiation Protocol*, *User*

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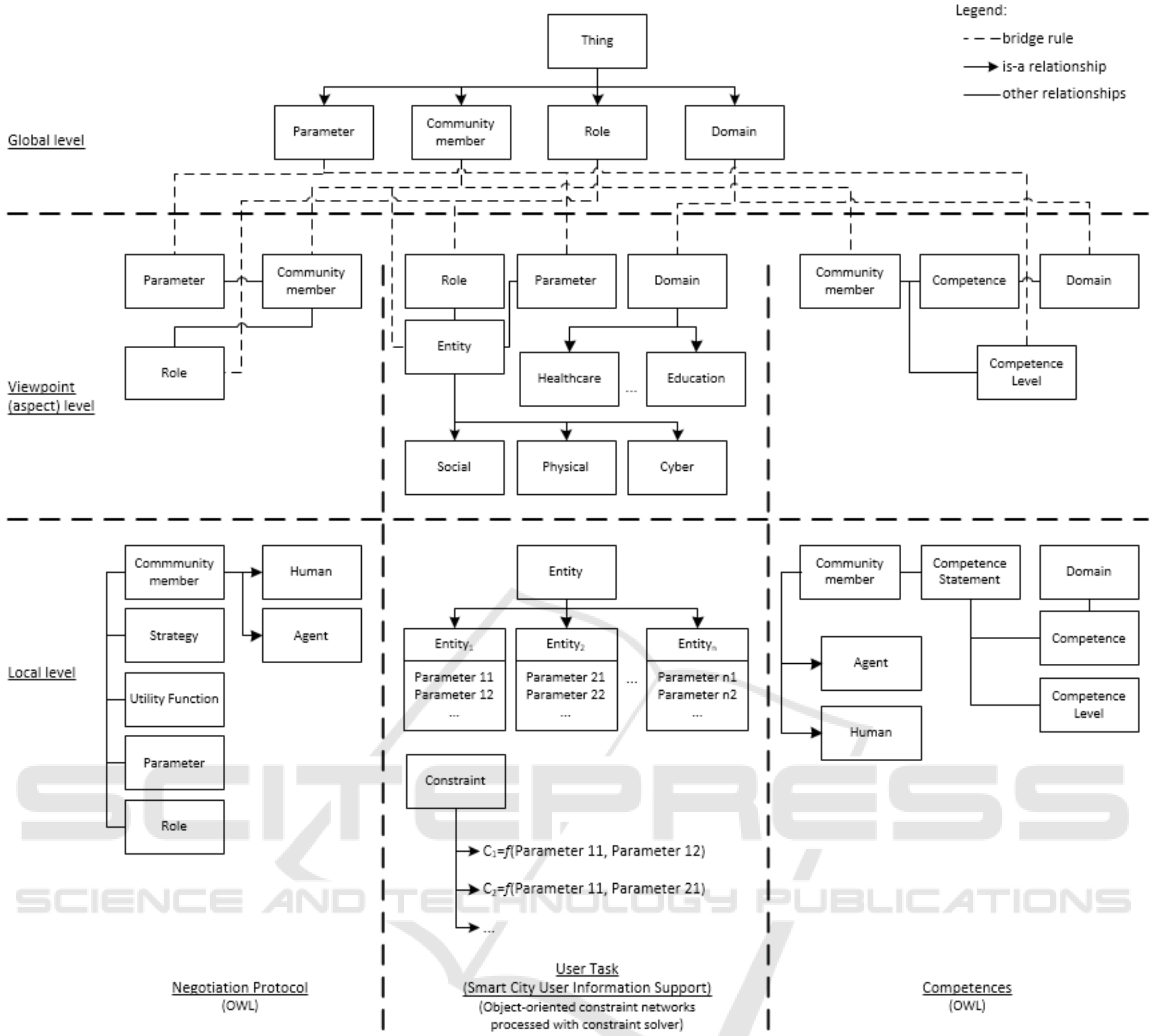

Figure 2: Multi-aspect ontology for three viewpoints.

Task. 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 behaviours 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 (Wang, Wong and Wang 2013), (Tamma et al. 2005). The formalism used in this aspect is OWL, and the example classes are *Community Member* (agent (representing software service) or human participant of the community providing for collective intelligence; subject of the negotiation process), *Human* (subclass of *Community Member*), *Agent* (subclass of *Community Member*), *Strategy* (outlines the overall coordination method governing the set of negotiation interactions), *Utility Function* (specifies the method to evaluate a proposal comprising multiple negotiation issues), *Parameter* (various variables affecting the negotiation process) and *Role* (played by the community members involved in a negotiation process).

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 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 *Competence* 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 (Brandmeier et al. 2017)). In this aspect, an OWL ontology is used.

In accordance with (Hemam and Boufaïda 2011) the following ontology elements have been defined:

Aspects: *Competence*, *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 are presented in Figure 3.

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 CONCLUSIONS

The paper suggests a methodology for building multi-aspect ontologies for interoperability support in a collective intelligence community aimed for decision support. The suggested methodology consists of six steps: interoperability requirements definition, aspect definition, development of aspect ontologies, aspect integration, verification, and validation.

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

Figure 3: Bridge Rules.

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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REFERENCES

Ahmed, S., Kim, S. and Wallace, K.M., 2005. A Methodology for Creating Ontologies for Engineering Design. In: *Volume 3: 25th Computers and Information in Engineering Conference, Parts A and B.* 2005 ASME. pp. 739–750. DOI: https://doi.org/10.1115/DETC2005-84729.

Anagnostopoulos, A., Broder, A.Z., Gabrilovich, E., Josifovski, V. and Riedel, L., 2007. Just-in-time contextual advertising. In: *Proceedings of the sixteenth ACM conference on Conference on information and knowledge management - CIKM '07*. 2007 New York, New York, USA: ACM Press. p. 331. DOI: https://doi.org/10.1145/1321440.1321488.

Azevedo, C.L.B., Almeida, J.P.A., van Sinderen, M., Quartel, D. and Guizzardi, G., 2011. An Ontology-Based Semantics for the Motivation Extension to ArchiMate. In: *2011 IEEE 15th International Enterprise Distributed Object Computing Conference*. August 2011 IEEE. pp. 25–34. DOI: https://doi.org/10.1109/EDOC.2011.29.

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Bonabeau, E., 2009. Decisions 2.0: The power of collective intelligence, *MIT Sloan Management Review*, 50(2): 44–53.

van den Bosch, K. and Bronkhorst, A., 2018. Human-AI cooperation to benefit military decision making. In: *Proceedings of Specialist Meeting Big Data & Artificial Intelligence for Military Decision Making*. 2018 p. DOI: https://doi.org/10.14339/STO-MP-IST-160.

Brandmeier, M., Neubert, C., Brossog, M. and Franke, J., 2017. Development of an ontology-based competence management system. In: *2017 IEEE 15th International Conference on Industrial Informatics (INDIN)*. July 2017 IEEE. pp. 601–608. DOI: https://doi.org/10.1109/INDIN.2017.8104840.

Calegari, S. and Ciucci, D., 2010. Granular computing applied to ontologies, *International Journal of Approximate Reasoning*, 51(4): 391–409. DOI: https://doi.org/10.1016/j.ijar.2009.11.006.

Darlington, M.J. and Culley, S.J., 2008. Investigating ontology development for engineering design support, *Advanced Engineering Informatics*, 22(1): 112–134. DOI: https://doi.org/10.1016/j.aei.2007.04.001.

Dustdar, S., Nastić, S. and Šćekić, O., 2017. *Smart Cities*. Cham: Springer International Publishing. DOI: https://doi.org/10.1007/978-3-319-60030-7.

Espinoza, M., Montiel-Ponsoda, E. and Gómez-Pérez, A., 2009. Ontology localization. In: *Proceedings of the fifth international conference on Knowledge capture - K-CAP '09*. 2009 New York, New York, USA: ACM Press. pp. 33–40. DOI: https://doi.org/10.1145/1597735.1597742.

European Commission, 2017. *New European Interoperability Framework: Promoting seamless services and data flows for European public administrations*. 2017.

Fazel-Zarandi, M. and Fox, M., 2012. An ontology for skill and competency management. In: *Formal Ontology in Information Systems. Frontiers in Artificial Intelligence and Applications*. IOS Press. p.

Fernández-López, M. and Gómez-Pérez, A., 2002. Overview and analysis of methodologies for building ontologies, *The Knowledge Engineering Review*, 17(2): 129–156. DOI: https://doi.org/10.1017/S0269888902000462.

Gallacher, S., Papadopoulou, E., Abu-Shaaban, Y., Taylor, N.K. and Williams, M.H., 2014. Dynamic context-aware personalisation in a pervasive environment, *Pervasive and Mobile Computing*, 10: 120–137. DOI: https://doi.org/10.1016/j.pmcj.2012.11.002.

Glenn, J.C., 2013. Collective Intelligence and an Application by The Millennium Project, *World Futures Review*, 5(3): 235–243. DOI: https://doi.org/10.1177/1946756713497331.

Gruber, T., 2008. Collective knowledge systems: Where the Social Web meets the Semantic Web, *Journal of Web Semantics*, 6(1): 4–13. DOI: https://doi.org/10.1016/j.websem.2007.11.011.

Halpin, H., Robu, V. and Shepherd, H., 2007. The complex dynamics of collaborative tagging. In: *Proceedings of the 16th International WWW Conference*. 2007 p.

Hemam, M., 2018. An Extension of the Ontology Web Language with Multi-Viewpoints and Probabilistic Reasoning, *International Journal of Advanced Intelligence Paradigms*, 10(1): 1. DOI: https://doi.org/10.1504/IJAIP.2018.10003857.

Hemam, M. and Boufaïda, Z., 2011. MVP-OWL: a multi-viewpoints ontology language for the Semantic Web, *International Journal of Reasoning-based Intelligent Systems*, 3(3/4): 147. DOI: https://doi.org/10.1504/IJRIS.2011.043539.

Lafleur, M., Terkaj, W., Belkadi, F., Urgo, M., Bernard, A. and Colledani, M., 2016. An Onto-Based Interoperability Framework for the Connection of PLM and Production Capability Tools. In: *PLM 2016: Product Lifecycle Management for Digital Transformation of Industries*. 2016 Springer. pp. 134–145. DOI: https://doi.org/10.1007/978-3-319-54660-5_13.

Lévy, P., 2010. From social computing to reflexive collective intelligence: The IEML research program, *Information Sciences*, 180(1): 71–94. DOI: https://doi.org/10.1016/j.ins.2009.08.001.

López-Gil, J.-M., Gil, R. and García, R., 2016. Web Ontologies to Categorialy Structure Reality: Representations of Human Emotional, Cognitive, and Motivational Processes, *Frontiers in Psychology*, 7: . DOI: https://doi.org/10.3389/fpsyg.2016.00551.

Miranda, S., Orciuoli, F., Loia, V. and Sampson, D., 2017. An ontology-based model for competence management, *Data & Knowledge Engineering*, 107: 51–66. DOI: https://doi.org/10.1016/j.datak.2016.12.001.

Smirnov, A. and Shilov, N., 2013. Ontology matching in collaborative recommendation system for PLM, *International Journal of Product Lifecycle Management*, 6(4): 322–338. DOI: https://doi.org/10.1504/IJPLM.2013.063210.

Tamma, V., Phelps, S., Dickinson, I. and Wooldridge, M., 2005. Ontologies for supporting negotiation in e-commerce, *Engineering Applications of Artificial Intelligence*, 18(2): 223–236. DOI: https://doi.org/10.1016/j.engappai.2004.11.011.

Tamma, V., Wooldridge, M., Blacoe, I. and Dickinson, I., 2002. An Ontology Based Approach to Automated Negotiation. In: *Agent-Mediated Electronic Commerce IV. Designing Mechanisms and Systems: AAMAS 2002 Workshop on Agent-Mediated Electronic Commerce*. 2002 pp. 219–237. DOI: https://doi.org/10.1007/3-540-36378-5_14.

Terziyan, V., Gryshko, S. and Golovianko, M., 2018. Patented intelligence: Cloning human decision models for Industry 4.0, *Journal of Manufacturing Systems*, 48: 204–217. DOI: https://doi.org/10.1016/j.jmsy.2018.04.019.

Wang, G., Wong, T.N. and Wang, X., 2013. An ontology based approach to organize multi-agent assisted supply chain negotiations, *Computers & Industrial Engineering*, 65(1): 2–15. DOI: https://doi.org/10.1016/j.cie.2012.06.018.

Yin, Y.H., Nee, A.Y.C., Ong, S.K., Zhu, J.Y., Gu, P.H. and Chen, L.J., 2015. Automating design with intelligent human–machine integration, *CIRP Annals*, 64(2): 655–677. DOI: https://doi.org/10.1016/j.cirp.2015.05.008.