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Management of Knowledge Intelligence in Human-centered Cyber Physical Production Systems

HABILITATIONSSCHRIFT

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Management of Knowledge Intelligence in Human-centered Cyber Physical Production Systems

Habilitationsschrift

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… to Marjan and Nick!

Preface

Industrial Engineering (IE) as defined by the Institute of Industrial and Systems Engineers (IISE) is a field "concerned with the design, improvement and installation of integrated systems of people, materials, information, equipment and energy. It draws upon specialized knowledge and skill in the mathematical, physical, and social sciences together with the principles and methods of engineering analysis and design, to specify, predict, and evaluate the results to be obtained from such systems"[1,2]. The IE body of knowledge[3] is represented by 14 areas, namely: 1) Work Design & Measurement, 2) Operations Research & Analysis, 3) Engineering Economic Analysis, 4) Facilities Engineering & Energy Management, 5) Quality & Reliability Engineering, 6) Ergonomics & Human Factors, 7) Operations Engineering & Management, 8) Supply Chain Management, 9) Engineering Management, 10) Safety, 11) Information Engineering, 12) Design & Manufacturing Engineering, 13) Product Design & Development, and 14) System Design & Engineering.

Integral aspects of IE as an interdisciplinary field are i) to apply engineering and management principles for effective planning, efficient operation, and productive management of a socio-technical system[4], and ii) to ensure optimal performance dealing with complex decision-making endeavors, i.e. making an optimal decision when confronted "uncertainty in achieving a desired set of functional requirements" [5].

The emergence of data-driven processes and intelligent entities (artificial intelligence (AI) agents, collaborative robots, etc.) raises questions about "Bounded Rationality", i.e. "a rational choice that takes into account the cognitive limitations of the decision-maker; limitations of both knowledge and computational capacity"[6]. In the light of digitalization, Industry

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[1] IISE, The Industrial Engineering, Body of Knowledge, Institute of Industrial and Systems Engineers, 2019, Available online at https://www.iise.org/Details.aspx?id=43631 (Accessed on 16.07.2019).

[2] In engineering education in German-speaking countries, IE is the most commonly used translation of the term "Wirtschaftsingenieurwesen". "Production Engineering and Management", "Industrial Engineering and Management" and "Engineering Management" are also interchangeably used to refer to IE.

[3] Cf. Footnote 1

[4] Baxter, G., & Sommerville, I. (2011). Socio-technical systems: From design methods to systems engineering. Interacting with computers, 23(1), 4-17.

[5] ElMaraghy, W., ElMaraghy, H., Tomiyama, T., & Monostori, L. (2012), Complexity in engineering design and manufacturing. CIRP annals, 61(2), pp. 793-814.

[6] Simon, H. A. (1990). Bounded rationality, In Utility and probability. Palgrave Macmillan, London, pp. 15-18.

4.0 and revival of AI, the concept of knowledge and knowledge actor (also referred to as decision-maker, problem-solver and learner) is evolved, i.e. intelligentization introduces new possibilities for creation, usage, sharing and preservation of knowledge through human and machine interaction and hybridization. In the context of smart and cognitive manufacturing, IE deals with optimization of cyber physical (systems of) systems in both design and operation phases, thereby its scope is extended to optimization of industrial management systems incorporating various modes of humans and intelligent machines communications, interactions and collaborations.

This habilitation thesis consists in putting forward the concept of "*Modeling and Management of Human-Machine Collective Knowledge Intelligence*" as a novel thematic area and an essential, future-oriented aspect of IE in both academic research and engineering education.

At the Vienna University of Technology (TU Wien), research, teaching and learning are conducted under the motto "Technology for People" (In German: Technik für Menschen) for over 200 years. The portfolio of the Institute of Management Science (IMW) represents various aspects of management related to digitalized world of works as well as design and management of socio-technical cyber-physical systems. The research landscape of IMW is comprised of five cluster topics (CT), namely: CT-1: Automation and Robotics, CT-2: Emerging Digital Technologies, CT-3: Leadership and Learning, CT-4: Sustainable Cyber Physical Systems, and CT-5: Technology Assessment. The aforementioned CTs cover 11 research themes including i) Production, Logistics and Maintenance Management, ii) Advanced Industrial Engineering, iii) AI and Knowledge Management in Cyber-Physical Production Systems, iv) New Ways of Working and Workspace Management, v) Human-Robot Collaboration, vi) IT-based Management, vii) Digital Assistance Systems, viii) Financial Enterprise Management, ix) Enterprise Risk Management, x) Gender in Science & Technology, and xi) Social and Societal Implications of Digitalization.

Yet, the potentials of Knowledge Management (KM), AI-driven and Knowledge-Based Methodologies for integrating intelligent functions into industrial value chain towards productive management of industrial systems of the future remains unexhausted. Hence, this habilitation thesis contributes into CT-1, CT-2 and CT-3 (Learning), and CT-4, and advances the IMW's body of knowledge, i.e. research and teaching portfolios, primarily in the thematic areas of "AI and Knowledge Management in Cyber-Physical Production Systems", "Production and Maintenance Management", "Human-Machine Collaboration", and "Knowledge-Based Learning and

Assistance Systems".

During postdoctoral time (since January 2015), the author has been undertaking efforts to establish his interdisciplinary research- and teaching portfolio on the boarder of IE, KM and AI. This habilitation thesis consolidates part of the outcomes and contributes to the field of IE by reconsidering and further developing the concept of managing human-machine collective knowledge intelligence, i.e. focusing on human and machine as a knowledge actor.

In particular, several initiatives and collaborations have been established with international academic partners and scientists from diverse fields such as IE, mechanical engineering, computer science, human resource management, labor organization and lifelong learning, which led to enriching the present habilitation thesis.

Furthermore, this work gains benefit from several European- and domestic funded research projects that have been conducting at the University of Siegen (2014-2016) and TU Wien (since 2017). Those are acknowledged in related publications.

It is worth noting that, the core concepts and key findings presented in this habilitation thesis have laid the ground for establishing the lecture and associated exercise of "*Knowledge Management in Cyber Physical Production Systems*" at the TU Wien, and the specialization of "*Production Information Management*" as part of the Master's program of Mechanical Engineering-Management at the Faculty of Mechanical and Industrial Engineering. In addition, a new chapter in the course of "Instandhaltungs- und Zuverlässigkeitsmanagement" (Maintenance and Reliability Management) is introduced, namely Knowledge-Based Maintenance, since winter semester 2017. As a visiting lecturer at the school of economic disciplines of the University of Siegen, several aspects and key findings of this habilitation thesis have been also integrated in the master seminar of "Industry 4.0: From Vision to Reality", since 2017.

Despite all accomplishments, Avicenna said, "the knowledge of anything, since all things have causes, is not acquired or complete unless it is known by its causes"[7]. Hence, research and education remain everlasting!

Dr.-Ing. Fazel Ansari Vienna, April 2020

[7] Avicenna, On Medicine, c. 1020 CE

Table of Contents

Introduction

I. Management of Human-Machine Collective Knowledge Intelligence: Foundation and Terminologies

Since 1950, when Alan Turing proposed to consider the question "*Can machines think?*" (Turing, 1950), enormous efforts have been invested in understanding and providing "satisfactory operational definition of intelligence", i.e. artificial intelligence (AI). Scientific evidences have been provided to support and validate the theory that machines can think and act humanly (Russell & Norvig, 2016). Given a satisfactory answer to the aforementioned question, intelligent functions are integrated in industrial value chain (Zhang et al., 2019). In the light of enhancing sensing and computational technology, intelligent connectivity, big data and knowledge intelligence as well as machine depth learning and cognitive computing, operation management strategies, production and business processes, manufacturing enterprises and service industry are undergoing substantial changes and transformations (aka Industry 4.0).

In this era, the Latin aphorism "scientia potestas est" meaning "knowledge is power", the famous equation coined by Francis Bacon in 1597, is still true. However, undeniable questions have been raised about the theoretical foundation (i.e. ontological and epistemological aspects) of knowledge and knowledge actor, and their influence on modeling "*Bounded Rationality*"[8] (cf. Simon, 1990) in (complex) decision-making. Furthermore, the well-founded theoretical principle of Knowledge Management (KM) to differentiate *human-oriented KM* (focusing on individual and organizational knowledge) from *technology-oriented KM* (dealing with tools and platforms) (cf. Maier, 2007) cannot anymore explain and solve problems in dynamic, data-driven and hybrid human-machine working environments and enterprises.

KM, briefly, is a productive series of iterative, life cyclic, dynamic and systematic exploitation and exploration activities and processes, which aim to make information actionable and reusable (Maier, 2007; Eppler, 2006). The term knowledge refers to a certain typology for distinction between explicit, tacit and latent knowledge. Explicit knowledge "is or could be expressed

[8] "Bounded Rationality" is concerned with a rational choice that takes into account the cognitive limitations of the decision-maker; limitations of both knowledge and computational capacity (cf. Simon, 1990).

without attenuation” (Wijnhoven, 2006). Tacit knowledge is a person-dependent knowledge (personal knowledge). This type of knowledge is not and cannot be expressed. Latent knowledge “could be expressed but it is difficult to express it without attenuation” (Wijnhoven, 2006). In practice, knowledge is mostly seen as explicit or implicit. The iceberg metaphor[9] helps to describe the aforementioned categories by identifying whether or not knowledge is represented, documented and/or codified. In particular, undocumented or non-codified knowledge such as personal experience or soft skills are considered as implicit, i.e. tacit or latent that are not (fully) visible and needs to be extracted, documented or discovered using certain methodologies like experience management, observation, interview, etc.

Besides, the term “Knowledge Based System” (KBS) is often used in the literature of AI and computer science as a technology to facilitate KM processes and enable knowledge exploitation and exploration functions. KBS refers to an intelligent information system in which “Knowledge” is represented and made usable with methods of knowledge representation and modeling (Russell & Norvig, 2016; Beierle & Kern-Isberner, 2014). In other words, a KBS consists of a set of methods to supply the systematic KM processes for representation, provision and application of knowledge in reasoning, prediction and prescriptive decision-making activities, where new knowledge is semantically linked to prior knowledge in a Knowledge-Base (KB). A KBS typically consists of four core components: (1) Knowledge acquisition, (2) Knowledge representation, (3) Knowledge modeling, and (4) Dialogue system (User interface), where the acquisitions, representation and modeling could be carried out by means of domain experts and knowledge engineers (manual), by means of intelligent algorithms (automatic), or combination of experts and algorithms (semi-automatic).

“*Knowledge acquisition* is the extraction of knowledge from sources of expertise and its transfer” to the KB (Turban, Aronson & Liang, 2005). Knowledge acquisition methods are classified into three categories as: (1) Manual e.g. by means of interview, analysis of protocols, observation, case studies, brainstorming, etc., (2) Semi-automatic by direct support and influence of domain experts, and (3) Automatic by means of algorithms and thus minimizing or eliminating the role of experts or knowledge engineers. The so-called knowledge engineer is

[9] As an iceberg floats in the water, the huge mass of it remains below the surface. The part of the iceberg is immediately visible; part of it emerges and submerges with the tides, and its foundations go deep beneath the surface.

responsible to construct the KBS. Using manual or semi-automatic methods, a knowledge engineer has a considerable role to be in contact with domain experts to submit questions, data and problems and to receive knowledge, concepts and solutions to be delivered to KB. KB is a warehouse, which contains the required knowledge for formulating and solving problems with formalized structure (Russell & Norvig, 2016; Beierle & Kern-Isberner, 2014). It provides the means for collection, organization, and retrieval of knowledge by establishing semantics between entities.

Knowledge representation includes two major forms, declarative or procedural (Russell & Norvig, 2016; Beierle & Kern-Isberner, 2014). In declarative representations, knowledge is stored as facts that must be interpreted, and it is accessible for a variety of purposes, while in procedural representations, knowledge is codified and stored as algorithms (program codes), thereby it is usable only within specialized problem-solving contexts (Russell & Norvig, 2016; Beierle & Kern-Isberner, 2014). In comparison, procedural representation is highly efficient in the correct context. Knowledge representation methods are e.g. predicate logic, rules, frames and scripts, ontologies, knowledge graphs or semantic networks.

Knowledge modeling are procedures for working with the knowledge stored in the KB, and mapping of the knowledge to fulfill certain tasks. It supports the acquisition and structuring of knowledge, formalization of knowledge for building KB, processing for solving a problem, e.g. using inference engine, visualizing of the knowledge and so on (Russell & Norvig, 2016; Beierle & Kern-Isberner, 2014).

Last but not least, a *dialogue system* utilizes a variety of knowledge sources and models. It is the main communication interface between users and KBS. The dialogue system is realized in the form of a graphical user interface, which encompasses a structure, mechanism, and procedures in the back-end for interpreting the entries of the user, matching them with the representation structure, and accordingly to provide an explainable output to the user.

II. Thematic Areas and Structure of Habilitation Thesis

In the age of rapid technological innovation and change, KM is a key enabler for value creation. Indeed, managing collective knowledge intelligence is of the utmost importance in achieving and sustaining business values especially increasing and maintaining (labor) productivity. Despite the efforts to reflect KM contributions to organizational learning, KM in the era of Industry 4.0 (aka KM 4.0) has not been widely and specifically studied, and is often limitedly interpreted in relation to four typical areas namely:

i) data sources, data streams and data collection, i.e. which types of data can be collected in (near real-time) e.g. by means of wireless- and sensory systems,

ii) data management platforms, i.e. how the scalable data in heterogeneous structures should be stored,

iii) data-driven methodologies, i.e. how to acquire knowledge (actionable information) from data, and

iv) data-mining procedures, i.e. which methods of supervised, semi-/unsupervised data mining and machine learning are appropriate to precisely and accurately explore (new) knowledge.

In all abovementioned areas, the common – but not comprehensively addressed- attribute is "Knowledge" required for reasoning, prediction (i.e. reasoning under uncertainty), and prescriptive decision-making. The key to achieve reliable, quality and informed decisions is discovering hidden patterns and semantic relations between knowledge attributes and iteratively linking new knowledge to prior (domain) knowledge stored in KBs. Furthermore, the human perspective on knowledge and KM cannot be ignored, especially with regard to the following societal challenges:

- Learning, i.e. which forms of learning are emerging, e.g. reciprocal learning through interaction of humans and machines; and subsequently which type of learning assistance systems are required,
- Vocational Education and Staff qualification, i.e. which (digital) skills and competences are emerging and/or denying, and thus how the education systems support skilling, reskilling and upskilling of existing and future human workforces, especially white- and blue-collars, and
- Job transformation and Job-Knowledge management, i.e. which tasks are assigned to humans and/or machines, what the shared tasks are, what the knowledge prerequisites are, and subsequently who is the responsible problem-solver and decision-maker.

Reconsideration of the concept of KM in smart factories, therefore, is not limited to the four areas above. It should necessarily reexamine both human- and technology (data and machine)-oriented perspectives of KM and the diagonal line across them. Notable affecting factors are as follows:

- proliferation of digital technologies,
- expansion of data space,
- emergence of human-centered cyber physical production systems (CPPS)
- advancement of virtual, digital and physical assistance systems, and
- deep integration of AI technologies and industrial processes, which introduce intelligent functions (e.g. autonomy, self-learning, and self-control) and new concepts of human-machine partnership and team formation (e.g. by means of collaborative robots and digital or virtual assistance systems) (cf. (Porter & Heppelmann, 2014; Schumacher et al., 2016; Davenport & Kirby, 2016; Zhang et al., 2019)).

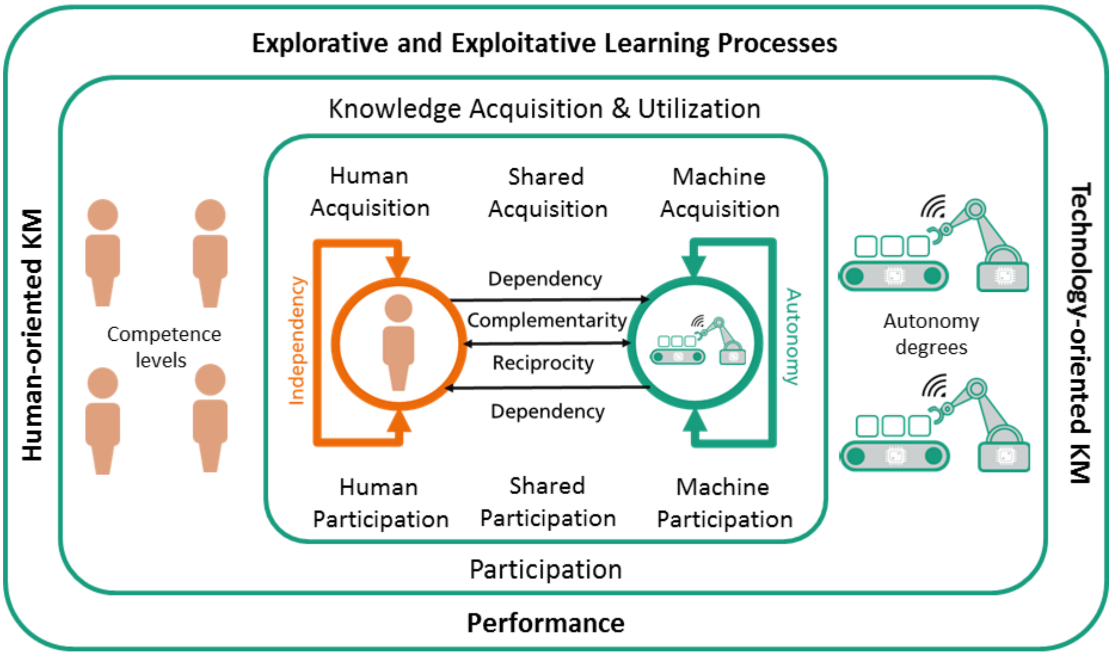

Figure 1. Boundary System for KM in the era of Industry 4.0: Hybridization of human and machine elements

Figure 1 depicts the boundary system for KM 4.0 in the CPPS, for example in human-robot collaboration within cyber physical assembly systems. The hybridization of knowledge actors compounds i) elements of human and machine in knowledge acquisition and utilization, and ii) job performance determinants, i.e. factors which affect participating in doing the (shared) tasks, into a new boundary system. The new boundary system is indicated with demarcated but flexible boundaries, i.e. boundary dynamics. It, therefore, allows both groups of workforce to participate in shared tasks (as an extension of shared workplace) and consequently defines new relation and exchange modes, namely reciprocity.

Yet, two interconnected aspects and thematic areas of KM are least discussed, has largely remained unexplored and even unnoticed within the production- and engineering management community, namely:

1) **Thematic Area I – Knowledge Management in CPPS (aka KM 4.0):** The emergence of "machine as a knowledge actor" beside human in CPPS (knowledge actors 4.0), i.e. complementarity and reciprocity of human- and technological entities (machines, robotic systems, Digital Twins, AI agents and algorithms) in smart factories.
2) **Thematic Area II – Knowledge-Based Methodologies and Approaches in CPPS:** The essence of rethinking and reconsidering operation and production management strategies to deal with the "Bounded Rationality" in complex decision-making, i.e. to overcome cognitive limitations of humans in decision-making by deploying knowledge-based methodologies and approaches as well as assistance systems for comprehensive knowledge acquisition, representation and modeling, especially for protecting collective knowledge intelligence by "Linking New Knowledge" to "Prior Knowledge".

This habilitation thesis focuses on both basic and applied-oriented research methodologies and is, therefore, intended…

I) to reconsider the concept of KM focusing on knowledge actors 4.0 and their interactions, i.e. creating, sharing, using and managing collective knowledge intelligence in dynamic, data-driven and hybrid human-machine working environments in smart factories.

II) to advance data-driven methodologies by applying knowledge-based methodologies (semantic modeling and analysis) and knowledge discovery from heterogeneous data sources (structured and unstructured knowledge) in particular by extracting hidden knowledge (e.g. from text) towards enriching knowledge repositories, facilitating integration of KM and production processes, and ultimately improving quality of decision-making.

The comprehensive research questions of this habilitation thesis with respect to the aforementioned objectives are:

I) “Can semantic modeling and analysis of human-machine collective knowledge intelligence in Cyber Physical Production Systems enhance to optimally identify jobholder profile (problem-solver, decision-maker) in maintenance and assembly systems by introducing qualitative and quantitative measures for characterizing job description, task and learning requirements, and thereby improve bidirectional matching of a jobholder to a job profile?” (Research Question I)

II) “Can integration of knowledge-based methodologies and production processes, in particular maintenance planning and operations as an integral part of production system, enhance processing of multi-modal and heterogeneous data collected from multidimensional data sources, and thereby generate decision support measures and recommendations for improving and optimizing forthcoming maintenance plans?” (Research Question II)

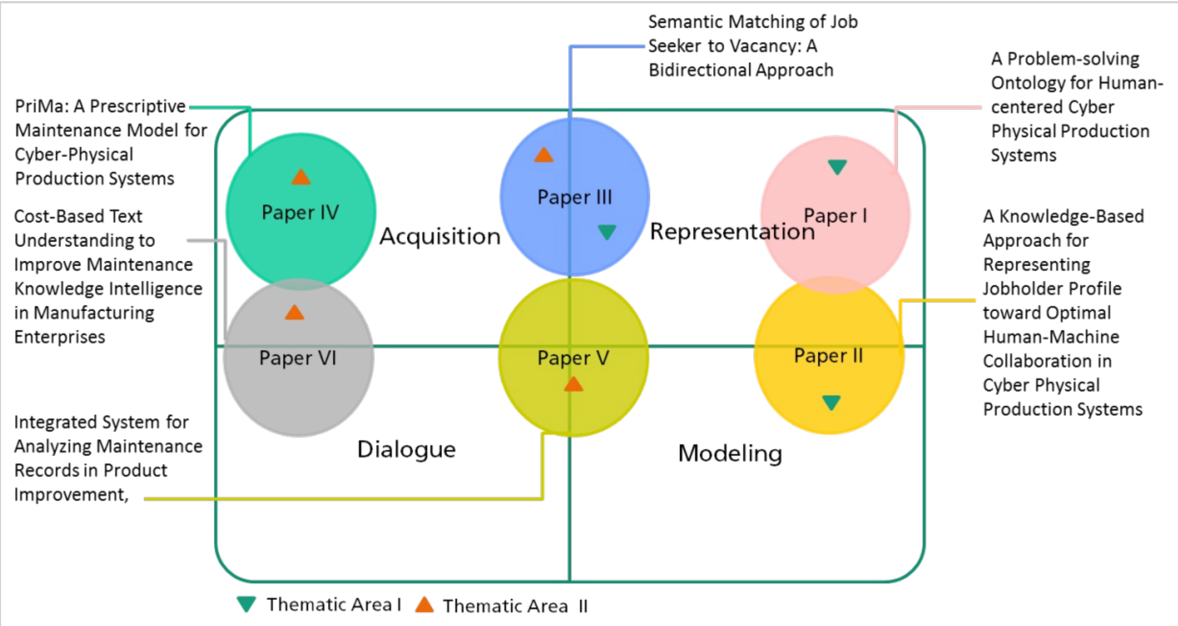

Figure 2. Methodical Focus of the papers according to four steps of knowledge-based methodology and thematic areas of the habilitation thesis

To address the aforementioned objectives, this habilitation thesis is structured in two Chapters, where in each chapter firstly a monograph is given, which portraits the author’s account on the thematic area. Secondly, selected publications appear which address segments of the guiding research questions of each thematic area, respectively. The portfolio matrix presented in Figure 2 identifies the methodical focus of each paper concerning four primary aspects of knowledge-based methodology (acquisition, representation, modeling and dialogue) as well as the contribution to the central research questions of the habilitation thesis. Furthermore, a deeper overview of selected publications is given below, including specific research questions and applied methods as well as in Table 1.

Selected Publications of Thematic Area I (Chapter 1)

- **Paper I:** Ansari, F., Khobreh, M., Seidenberg, U., & Sihn, W. (2018). A Problem-solving Ontology for Human-centered Cyber Physical Production Systems, *CIRP Journal of Manufacturing Science and Technology*, 22, pp. 91-106.
    - Research Question: Can cyber-physical-socio space be semantically linked to construct a holistic model for identifying human and CPPS complementary in problem-solving processes?
    - Methodology: Qualitative modeling, i.e. ontology modeling and engineering with first-order logic (FOL) notations.
- **Paper II:** Ansari, F., Hold, P. & Khobreh, M., (2020). A Knowledge-Based Approach for Representing Jobholder Profile toward Optimal Human-Machine Collaboration in Cyber Physical Production Systems, *CIRP Journal of Manufacturing Science and Technology*, 28, PP. 87-106.
    - Research Question: How to establish a twofold qualitative and quantitative methodology for optimal selection of a competent jobholder(s) to perform a certain task by semantic modeling and analysis of jobholder (human and machine) profile corresponding to the task characteristics, required knowledge, skills and competences (KSCs) and learning requirements?
    - Methodology: Qualitative modeling with Ontology; Quantitative modeling by aggregating mathematical measures.
- **Paper III:** Chala, S. A., Ansari, F., Fathi, M., & Tijdens, K. (2018). Semantic Matching of Job Seeker to Vacancy: A Bidirectional Approach, *International Journal of Manpower*, 39(8), pp. 1047-1063.
    - Research Question: How to bi-directionally match a job seeker to vacancy by measuring the degree of semantic similarity of job-seeker qualifications and skills, against the vacancy advertisements provided by employers or job-agents, and assess the trend of changes (emergence/decline) of on the selected IoT and Industry 4.0 jobs?

- Methodology: Qualitative modeling of semantic similarity, mathematical modeling, Bidirectional matching, experimental validation.

Selected Publications of Thematic Area II (Chapter 2)

- **Paper IV:** Ansari, F., Glawar, R. & Nemeth, T. (2019). PriMa: A Prescriptive Maintenance Model for Cyber-Physical Production Systems, *International Journal of Computer Integrated Manufacturing*, Vol. 32, Issue 4-5: Smart Cyber-Physical System Applications in Production and Logistics, Taylor & Francis, pp. 482-503.
    - Research Questions:
        - From a conceptual and theoretical perspective: "How to discover and preserve maintenance knowledge in CPPS environment to enhance decision-making processes?"
        - From a practical perspective: "How to apply such a conceptual model in industrial use-cases where several technological and non-technological barriers exist?" Methodology: Qualitative modeling of semantic similarity, mathematical modeling, Bidirectional matching, experimental validation.
    - Methodology: Qualitative modeling, CRISP-DM, data-mining, text-mining, mathematical modeling, proof-of-concept with industrial use-case.
- **Paper V:** Dienst, S., Ansari, F., & Fathi, M. (2015). Integrated System for Analyzing Maintenance Records in Product Improvement, *International Journal of Advanced Manufacturing Technology*, 76(1-4), pp. 545-564.
    - Research Question: Can Dynamic Bayesian Networks enhance knowledge-based analysis of structured feedback data, including condition monitoring, service, and customer data, and predictive detection of improvement potentials in maintenance management and product improvement phase of product design?
    - Methodology: Mathematical Modeling, Dynamic Bayesian Networks, use-case study and validation.
- **Paper VI:** Ansari, F. (2020). Cost-Based Text Understanding to Improve Maintenance Knowledge Intelligence in Manufacturing Enterprises, Journal of Computers and Industrial Engineering, Vol. 141.

- Research Question: Can text mining support deeper understanding of maintenance reports by investigating both syntax and semantic levels, represent the text reports as a numeric values, discover maintenance cost data from textual reports, and thus provide additional measures for improving maintenance planning?
- Methodology: Qualitative and mathematical modeling, Text-Mining.

Table 1. Summary of the applied methods and results of the papers presented in Chapter I and II

	Paper	Methodology	Results
Chapter I	A Problem-solving Ontology for Human-centered CPPS	Ontology modeling and engineering with first-order logic (FOL) notations	PSP Ontology (Problem, Solution, Problem-Solver Ontology) formalized by introducing (i) contingency vector, (ii) vector of competence and autonomy, and (iii) solution maturity index
	A Knowledge-Based Approach for Representing Jobholder Profile toward Optimal Human-Machine Collaboration in CPPS	Ontology modeling; Quantitative modeling by aggregating mathematical measures	A twofold qualitative and quantitative methodology for optimal selection of a competent jobholder
	Semantic Matching of Job Seeker to Vacancy: A Bidirectional Approach	Qualitative modeling of semantic similarity, mathematical modeling, Bidirectional matching, experimental validation	A framework of an automatic bidirectional matching that measures the degree of semantic similarity of job-seeker qualifications and skills, against the vacancy provided by employers or job-agents.
Chapter II	PriMa: A Prescriptive Maintenance Model for CPPS	Qualitative modeling, CRISP-DM, data-mining, text-mining, mathematical modeling, proof-of-concept with industrial use-case	A Prescriptive Maintenance model (PriMa) comprising of four layers, i.e. data management, predictive data analytic toolbox, recommender and decision support dashboard as well as an overarching layer for semantic-based learning and reasoning.
	Integrated System for Analyzing Maintenance Records in Product Improvement	Mathematical Modeling, Dynamic Bayesian Networks, use-case study and validation	Dynamic Bayesian Network for K-Modeling linked to cost model for analyzing maintenance data and decision-making as well as a mobile App for maintenance engineers
	Cost-Based Text Understanding to Improve Maintenance Knowledge Intelligence in Manufacturing Enterprises	Qualitative and mathematical modeling, Text-Mining	A compositional framework for text understanding incl. Association Measuring Index (AMI), Opinion Index (OI) and Cost Vector (CV).

The remainder of this habilitation thesis is structured as follows: Chapter 1 and 2 provide detailed account of the author and selected publications on “Human and Machine as Knowledge Actor and Labor Force in CPPS” and “Knowledge-Based Maintenance”, respectively. Chapter 2 advances the scope of integrating knowledge-based methodologies in maintenance planning and operations.

References

Beierle, C. & Kern-Isberner, G. (2014). Methoden wissensbasierter Systeme: Grundlagen, Algorithmen, Anwendungen (Methods of Knowledge-Based Systems: Fundamentals, Algorithms and Applications), Springer.

Eppler, M. J. (2006). Managing information quality: Increasing the value of information in knowledge-intensive products and processes. Springer Science & Business Media.

Maier, R. (2007). Knowledge Management Systems, Information and Communication Technologies for Knowledge Management, 3rd Ed., Berlin, Germany: Springer, p. 57.

Russell, S. J., & Norvig, P. (2016). Artificial intelligence: a modern approach. Malaysia; Pearson Education Limited.

Simon, H. A. (1990). Bounded rationality, In Utility and probability, Palgrave Macmillan, London, pp. 15-18.

Turban, E., Aronson, J. E. & Liang, T.-P. (2005). Decision Support Systems and Intelligent Systems, Prentice Hall, 7th edition.

Turing, A. (1950). Computing machinery and intelligence. Mind, 59, pp. 433–460.

Wijnhoven, F. (2006). Knowledge Management: More than a Buzzword, Knowledge Integration: The practice of Knowledge Management in small and medium enterprises, pp. 1-16, 2006.

Zhang, X., Ming, X., Liu, Z., Yin, D., Chen, Z., & Chang, Y. (2019). A reference framework and overall planning of industrial artificial intelligence (I-AI) for new application scenarios. International Journal of Advanced Manufacturing Technology, 101(9-12), pp. 2367-2389.

Chapter 1: Human and Machine as Knowledge Actor and Labor Force in CPPS

1.1 Theoretical and Practical Considerations of Knowledge Management 4.0: Overview & Outlook[10]

1.1.1 Strategic and Operational Aspects

KM, concisely, is "the management function responsible for the regular selection, implementation and evaluation of goal-oriented knowledge strategies that aim at improving an organization's way of handling knowledge internal and external to the organization in order to improve organizational performance" (Maier, 2007). With this in mind, the question is: *What are the strategic and operational tasks of KM in the age of digital transformation?*

Recently, the concept of "Knowledge 4.0" and the model of "Knowledge Ladder 4.0" have been introduced by (North & Maier, 2018). They assume enhancing value creation in the digital knowledge economy is achieved through utilizing digital technologies for knowledge creation and sharing (North & Maier, 2018). The digital society and digitally enabled knowledge economy are, therefore, characterized by digitalization and intelligentization of everyday life and value creation (North & Maier, 2018), where smart and connected products, cognitive and networked systems, and AI are transforming the competition, professions and education (Porter & Heppelmann, 2014). The model of Knowledge Ladder 4.0 is based on the premise that digitalization and intelligentization extend the scope of knowledge from a set of discrete facts internalized by a receiver to ability, competence and competitive skills, i.e. Knowledge 4.0 (North & Maier, 2018). In particular, the job-knowledge consists of knowledge, skills, abilities and competences (KSACs) (cf. (Khboreh et al., 2016)) that an Industry 4.0 jobholder should be able to demonstrate.

Recent studies propose different types of taxonomy for classification of KSACs taking into account various roles of human in manufacturing environment (D'Antonio & Chiabert, 2018). Notable taxonomies are provided e.g. by (Hecklau et al., 2016; Piñol et al., 2017). The former identifies four necessary competence categories namely, technical, methodological, social and

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[10] The majority of Section 1.1 has been published in the following article: Ansari, F. (2019). Knowledge Management 4.0: Theoretical and Practical Considerations in Cyber Physical Production Systems, IFAC-PapersOnLine, Vol. 52, Issue: 13, pp. 1597-1602. (Link)

personal competences. The latter identifies skills required by Industry 4.0 employee, namely technological skills, skill techniques and soft skills.

From a strategic point of view, KM 4.0 can be envisaged as a "*Dynamizer*" to i) identify critical knowledge required e.g. for building new business models, acquiring future-oriented intellectual capitals and knowledge assets , ii) enable the creation of meaning and common undemanding as a basis for action, i.e. decision-making or problem-solving, iii) encourage innovation, active learning and reflections, and iv) build platforms for engaging internal and external stakeholders.

From an operational point of view, KM 4.0 is a "*Stabilizer*" to i) ensure ubiquitous and organized information and knowledge flows, ii) enable cross-sector cooperation, and iii) reconcile and harmonize human learning and machine learning as well as human-machine reciprocal learning, i.e. co-creation of collective intelligence (Ansari, Erol & Sihn, 2018).

1.1.2 Proposed Definition of KM in the context of Industry 4.0

The aforementioned definition of KM should be reconsidered in the light of digitalization and intelligentization of manufacturing industry (Zhou, 2013). KM in the era of Industry 4.0 (KM 4.0) either as a dynamizer or as a stabilizer should be approached from two distinct but interrelated perspectives, i.e. human- and technology-oriented perspectives.

From the author's point of view, KM 4.0 is a strategic and operational function comprising exploration and exploitation processes. KM 4.0 is responsible to accomplish the following tasks, namely i) continuously support value generation through enhancing and balancing need- or opportunity-driven knowledge generation and knowledge utilization capacities, and ii) persistently facilitate developing and protecting human-machine collective intelligence across manufacturing enterprises and in particular smart factories. The latter is demonstrated by advanced optimization, prediction, adaptation, and ideally self-learning capabilities embedded in knowledge-intensive processes, systems, tools and platforms. Hence, KM 4.0 is an enabler to maximize competitive advantages and derive business values in the manufacturing enterprises.

Figure 3 presents a portfolio matrix, where KM 4.0 is classified according to the correlative degree to which knowledge generation and knowledge utilization, including knowledge sharing, is accomplished by means of exploiting existing knowledge and exploring new knowledge. According to the exploitation and exploration degree, one may say that a KM function in a manufacturing enterprise is ideal when the Balance Point (BP) is achieved, i.e. maximum degree of knowledge generation and knowledge utilization. In real-world settings, BP is either shifted into shortage of exploitation or exploration processes. The former makes the KM more dynamic and the latter more stable. Radically shifting the BP triggers undesirable situations, where one may say that a KM function is a worse or imperfect. Worse KM occurs when both knowledge exploitation and exploration across an enterprise are inefficient and ineffective. Imperfect KM occurs when either knowledge exploitation or exploration is ineffective, i.e. focusing only on explorative learning or exploitative learning.

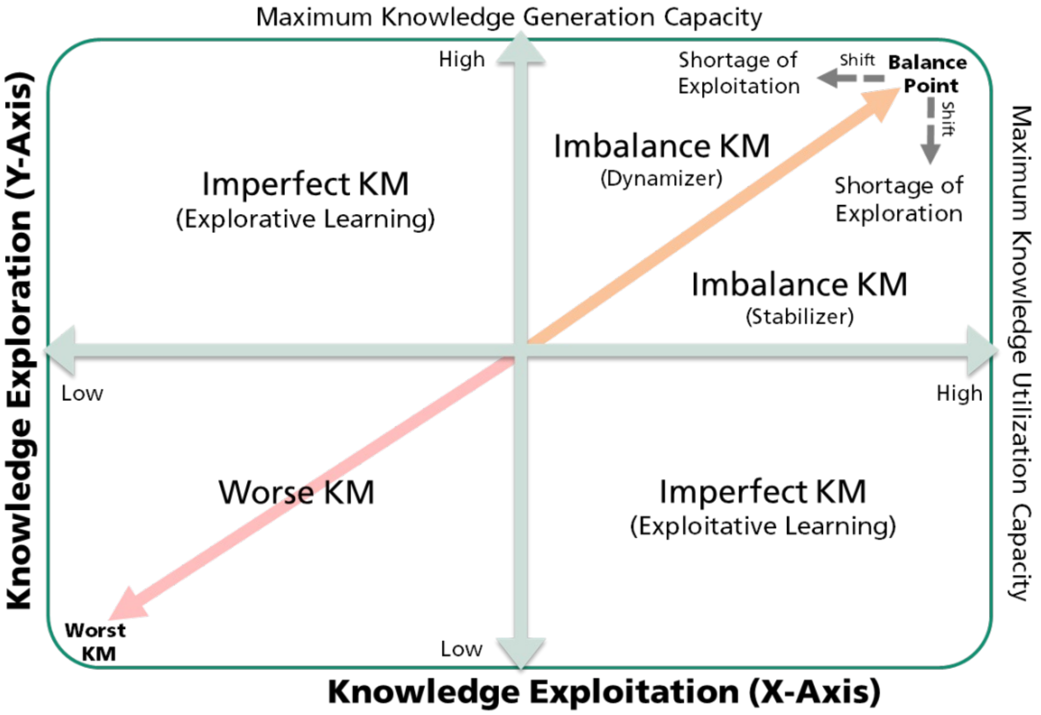

Figure 3. Portfolio Matrix for KM 4.0

1.1.3 Ontological and Epistemological Considerations

Imitating human capabilities, thinking or acting activities, by machines introduces the concept of "machine as a workforce" and subsequently "machine as a knowledge actor". What are the key considerations in human-machine settings?

Notably, machine in this context refers to a wide range of intelligent, autonomous, robotic and AI systems, which are able to reproduce human manual or cognitive capabilities partially or fully.

From an ontological point of view, human resources and machine workforces are complementary, especially by considering one's capabilities are superior or inferior to the other. Nevertheless, they are epistemologically distinct. Given the division of labor between humans and machines, KM 4.0 has to deal with two distinct groups of knowledge actors and five related instances or roles (where *K* refers to *Knowledge*), namely:

1) ***k-holder*** for explicating and storing knowledge,
2) ***k-producer*** for completing existing knowledge and creating new knowledge,
3) ***k-user*** for transforming knowledge to skills and testing knowledge in practice, e.g. by on-the-job training,
4) ***k-receiver*** for selecting and accepting knowledge before stored by k-holder; and finally
5) ***k-eraser*** for unlearning knowledge (cf. Section 1.1.6).

Each of the aforementioned roles is a part of learning. Thus, "learner" is the superordinate term involving learning, re-learning and unlearning.

Considering the participation of human and machine workforces in performing manual or cognitive tasks, especially in shared tasks, three fundamental issues should be considered:

I) How is the concept of knowledge actor in human-machine settings theorized?,
II) What are the possible relations between human and machine in hybrid settings?, and
III) How do human and machine acquire knowledge and develop the collective intelligence of a manufacturing enterprise?

1.1.4 Theoretical Implications

The hybridization may significantly affect the nature of knowledge acquisition, utilizations and in fact offers new division of tasks and labor as well as new symmetric or asymmetric associations between human and machine knowledge actors (cf. Figure 1 and 4). The concept of KM 4.0 encompasses two theoretical standpoints as follows:

1) **Complementarity** in knowledge creation and/or utilization whereby human and machine jointly participate in knowledge exploitation and exploration processes. Hence, human-machine reciprocal relation, mutual dependency, exchange and action may occur. In this setting, overlapping and shared tasks can be envisaged, thereby human and machine together accomplish a task.

2) **Substitutability** in knowledge creation and/or utilization whereby only human or machine participate in knowledge exploitation and exploration processes. Therefore, the dominant workforce is assigned to perform a (manual or cognitive) task[11].

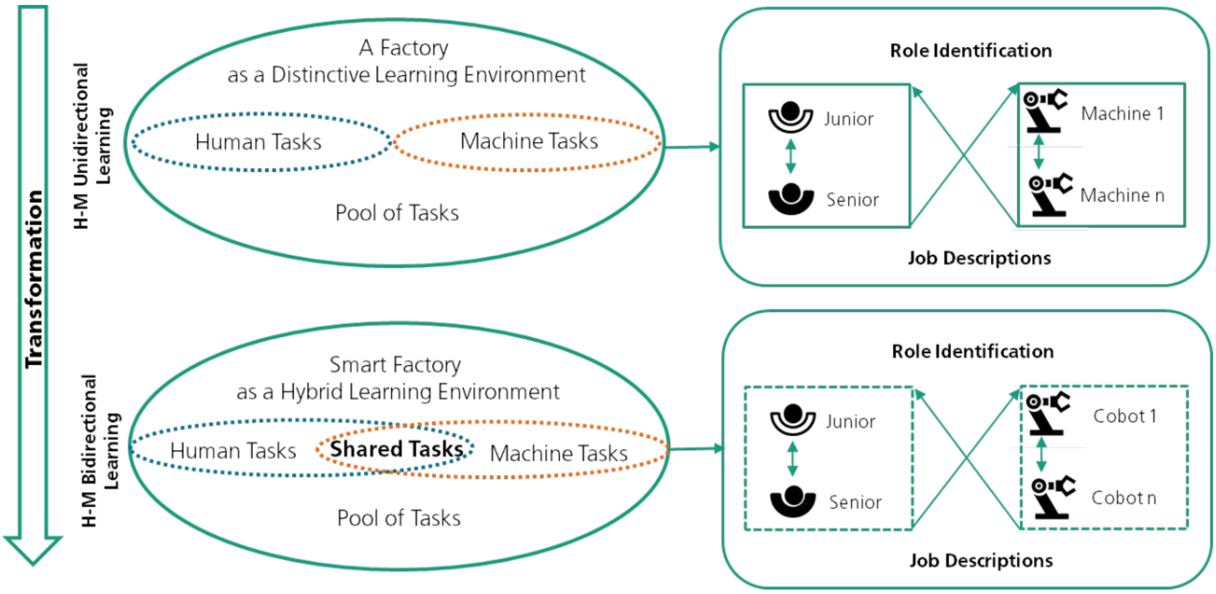

Figure 4. Hybridization of Human & Machine Elements and Emergence of Physical & Cognitive Dependencies

In real-world hybrid settings, assignment of tasks to human and/or machine is based upon the premise that each group of worker is capable of performing certain types of tasks, i.e. having the capabilities that are suitable for the specific task and purpose. Various task allocation approaches

I) identify human and machine capabilities,

II) classify the tasks according to required manual and cognitive capabilities, i.e. demand list,

III) divide the tasks into sub-tasks, i.e. assignments, and

IV) allocate assignments to suitable individual workers, i.e. human or machine.

The so-called function allocation, therefore, “provides a rational means of determining which system-level functions should be carried out by humans and which by machines” (Bradshaw et al., 2012). The most notable example for such demand-capability approaches is the model of HABA-MABA (humans-are-better-at/machines-are-better-at) originally introduced by (Fitts, 1951).

[11] Notably, various aspects (economic, ethical, ergonomic, etc.) of superordination and/or subordination of human or machine should be further investigated, especially when the self-image of human is affected, which is out of the scope of this habilitation thesis.

Moreover, the complementary of human and machines in CPPS environment can be examined considering their characteristics with regard to five criteria, namely: 1) cost, 2) flexibility with regard to fulfilment of various tasks and temporal availability, 3) capacity with regard to mechanical (physical) job, information processing and problem-solving, 4) performance variation, and finally 5) quality variation with regard to mechanical job and decision-making (cf. (Ansari et al., 2018b)). It seems that the term capability should be understood as an umbrella for human and machine representing all aforementioned characteristics, which help to find a common ground.

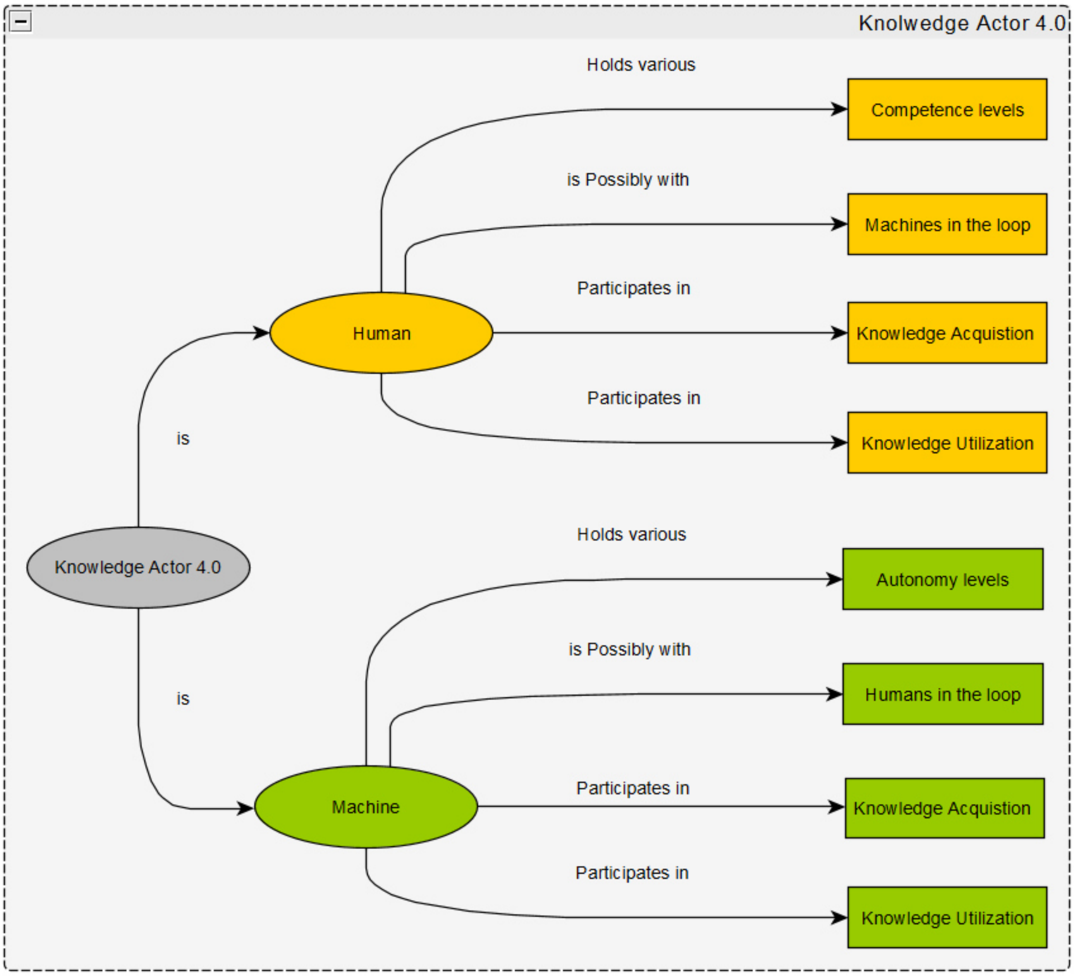

Figure 5. Meta-model for representing the concept of Knowledge Actor 4.0

Referring to the aforementioned distinction between two theoretical standpoints, complementarity versus substitutability of humans and machines, two different approaches can be identified, namely i) capability automatization and ii) adaptive function allocation. The former denotes AI-based approaches aim to reproduce human capabilities and maximize automation by means of algorithms; thereby machines can take over today's human jobs (cf. (Ansari, Erol & Sihn, 2018)). For instance, self-supervised deep learning approaches to robot learning are employed, which enable robots to grasp objects without involving human supervision (cf. (Sermanet et al., 2017; Levine & Sermanet, 2017)). In contrast, the latter, adaptive function allocation, aims to identify the adjustable and variable task assignments, where overlapping capabilities could help to define shared task (cf. (Michalos et al., 2018)) and ultimately increase (labor) productivity (cf. (Blohm et al., 2016; Khobreh, Ansari & Seidenberg, 2019)).

Focusing on the complementarity of the knowledge actors, Figure 5 depicts the meta-model for representing the concept of "Knowledge Actor 4.0" and related instances, namely human and machine.

Based on this assumption, knowledge base of a manufacturing enterprise should consist of a set of Digital Knowledge Profiles (*DKPs*) whose members are Human Digital Knowledge Profile ($HDKP$) and Machine Digital Knowledge Profile ($MDKP$). The DKPs specify the level of KSACs of each knowledge actor and are used to reveal the trajectory of learning over the time. Matching the DKP instances to the tasked sorted and labelled per expertise level (Expert, Intermediate and novice) by domain expert, identifies the role of human and/or machine as well as the extent of their participation in doing a (shared) task.

As an example, Figure 6 illustrates the schematic representation of the knowledge base of a smart factory and related matching function. In the knowledge base, the DKPs are represented and described as a vector form consisting supplied $\mathrm{KSAC_{ik}}$ as in

$$\overrightarrow{\mathrm{dkp}}_{\mathrm{Supply}} = (\mathrm{KSAC_{i0}}, \dots, \mathrm{KSAC_{ik}}) \tag{1}$$

Likewise, tasks classified and labelled per expertise levels of the workforces in the smart factory are described as a vector form consisting demanded $KSAC_{jk}$ as in

$$\overrightarrow{\mathrm{dkp}}_{\mathrm{Demand}} = (\mathrm{KSAC_{j0}}, \dots, \mathrm{KSAC_{jk}}) \tag{2}$$

where $i, j \in [0, k]$ indicating the number of KSACs that should be supplied by human or machine workforce in response to a demand inquiry provided by a planner. The matching function therefore measures the similarity between the supply and demand vectors using Cosine Similarity (Rahutomo et al., 2012), as in:

$$\mathrm{Sim}\left(\overrightarrow{\mathrm{dkp}}_{\mathrm{Demand}}, \overrightarrow{\mathrm{dkp}}_{\mathrm{Supply}}\right) = \frac{\overrightarrow{\mathrm{dkp}}_{\mathrm{Demand}} \cdot \overrightarrow{\mathrm{dkp}}_{\mathrm{Supply}}}{\left|\overrightarrow{\mathrm{dkp}}_{\mathrm{Demand}}\right| \cdot \left|\overrightarrow{\mathrm{dkp}}_{\mathrm{Supply}}\right|} = \frac{\sum_{k=0}^{t} \mathrm{KSAC_{ik}} \times \mathrm{KSAC_{jk}}}{\sqrt{\sum_{k=0}^{t} (\mathrm{KSAC_{ik}})^2} \cdot \sqrt{\sum_{k=0}^{t} \left(\mathrm{KSAC_{jk}}\right)^2}} \tag{3}$$

Values assigned to KSACs may range [0, 1], where 0 and 1 refers to poor and excellent level of representing a KSAC element such as a mechanical or analytical KSACs, respectively.

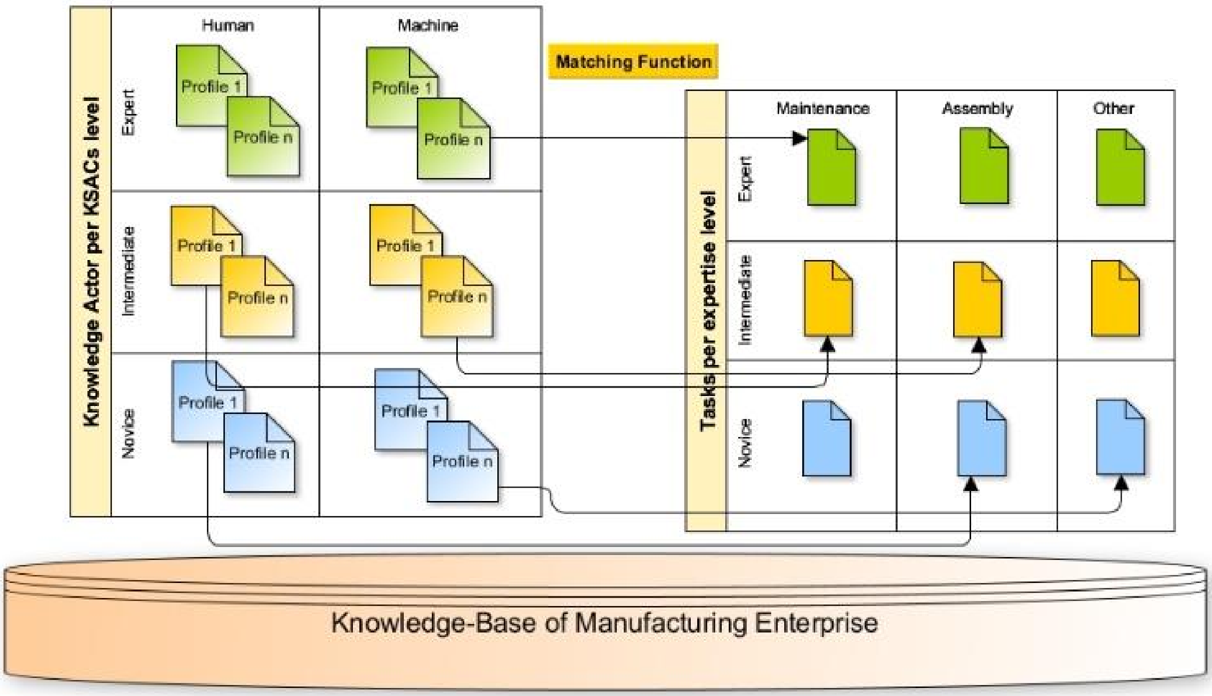

Figure 6. Knowledge Base of a Smart Factory

1.1.5 Practical Considerations

The following example illustrates how the previously mentioned matching function (cf. Section 1.1.4) supports a planner to assign a task to human or machine workforce in practice. Assume a task allocation problem for assembly of a product in a human-robot system. Task A (Assembly of product X) can be divided into sub-tasks, such as mechanical assembly (fastening, handling, calibrating), collecting data and quality control (checking). The sub-tasks should be accomplished in various sequences and may require various manual or cognitive capabilities. According to the classification of tasks per expertise level of the workforce, the demand vector is instantiated, which represents the required KSACs for fulfilling the assembly tasks. Either human and/or machine workforce according to predefined and labelled individual KSACs should supply the demanded KSACs. As illustrated in Figure 7 and 8, let us consider two options for assigning sub-tasks to human or machine workforces, without or with identification of shared tasks, respectively. In the first scenario, the planner makes an inquiry of all those human and machine workforces who provide KSACs including mechanical and analytical KSACs for fastening, handling, calibrating, checking and collecting data. Retrieving DKPs ordered based on the demand-supply matching, i.e. degree of similarity between demanded and supplied KSACs, the planner may select the best-fit human and machine profiles and distribute the sub-tasks.

For instance, assume that the domain expert initializes demand vector for representing the maximum KSACs required for an assembly task including mechanical sub-tasks (fastening, handling and calibrating) as well as data collection and quality control tasks as in $\overrightarrow{\mathrm{dkp}}_{\mathrm{Demand}} = (0.6, 0.7, 0.8)$, (under $k = 3$). The planner may employ the matching function to retrieve two workforce DKPs, representing a human and machine DKP supplying the demanded KSACs with similarity degree of 96% and 85%, as $\overrightarrow{dkp_1} = (0.5, 0.3, 0.4)$ and $\overrightarrow{dkp_2} = (0.3, 0.2, 0.4)$, respectively.

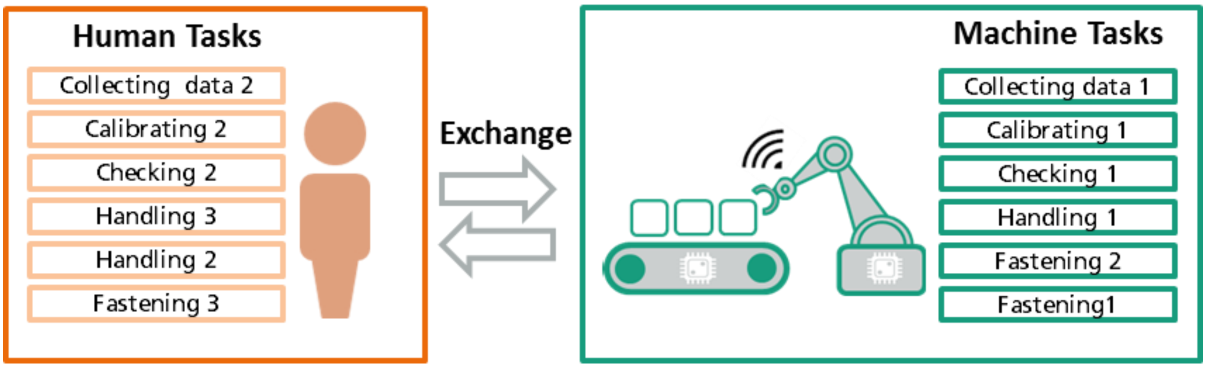

Figure 7. Assigning distinct tasks to Knowledge Actors 4.0

In the second scenario, the planner may repeat the matching processes e.g. by restricting the boundary conditions such as safety in which human and machine together can fulfil certain sub-tasks.

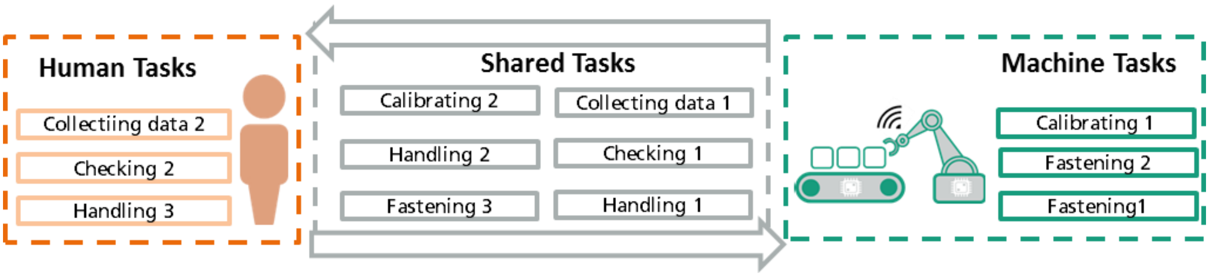

Figure 8. Assigning shared tasks to Knowledge Actors 4.0

Considering the above discussion, the planner requires a knowledge-based assistance system, which provides following components: i) knowledge-base consisting of DKPs and the supply-demand matching function, ii) decision engine including features to adaptively generate selection rules, and iii) recommender engine to identify measures and strategies to various production and business-oriented goals of a smart factory.

As illustrated in Figure 9, the goals are briefly defined as short-term goals for optimization of existing tasks and processes, mid-term for achieving new division of works between human and machine workforce, and long-term for enabling the smart factory, as a system of systems, to think and innovate new products and services. Such a learning recommender system should provide a kind of target function, which correlates labor productivity and learning effectiveness as a measure to identify knowledge imbalance, i.e. gaps and surplus, across the smart factory.

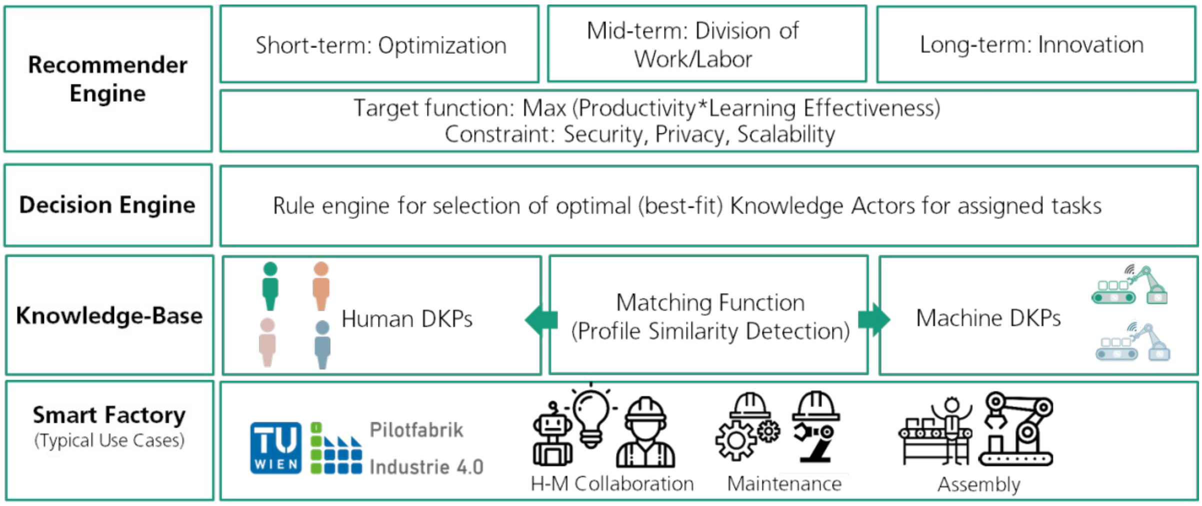

Figure 9. A Knowledge-Based Assistance System for selection of best-fit Knowledge Actor 4.0 – Adopted from (Ansari, et al., 2018a)

1.1.6 Critical Consideration: Learning vs. Unlearning of Knowledge

Looking again at the portfolio matrix for KM 4.0 (cf. Figure 3); one could argue that KM 4.0 focuses only on exploitative and explorative learning. This raises the critical question how to deal with “unlearning of knowledge”. In other words, organizational, community and individual KSCAs, which has been previously learned should not be necessarily considered or utilized for forthcoming activities, especially in a changeable manufacturing settings.

In Figure 3, the classification of KM into worse, imperfect and imbalance is according to degree of effectiveness and efficiency of knowledge exploitation and exploration activities, i.e. whether the BP is achieved or knowledge imbalance, gaps or shortage is avoided. From the author’s point of view, re-learning and unlearning of knowledge naturally occurs through explorative and exploitative learning. Furthermore, a recent literature review reveals the lack of “robust conceptual and empirical evidence to advance the field of unlearning and forgetting” across enterprises, even though it has gained increased attentions in the literature (Klammer & Gueldenberg, 2018). Thus, KM 4.0 encompasses the processes of identifying and discarding outdated (obsolescence) knowledge as undeniable part of continuous learning.

1.1.7 Outlook

Figure 10 summarizes future avenues for further research by providing determinants and factors, which affect implementation of KM 4.0. In particular, four research directions can be identified as:

I) **Job-Knowledge Management** should be investigated by focusing on job transformation, new divisions of labor, transformation of human jobs (including emergence of new human jobs) and introduction of automatable/automated jobs performed by machines and algorithms. The impact of job transformation and dynamics of jobs on KM 4.0 directly or indirectly affects creation of new types of knowledge and introduces new knowledge actors. Yet, empirical evidences are required to precisely identify cause-effect relations and to provide a valid list of controllable and uncontrollable factors.

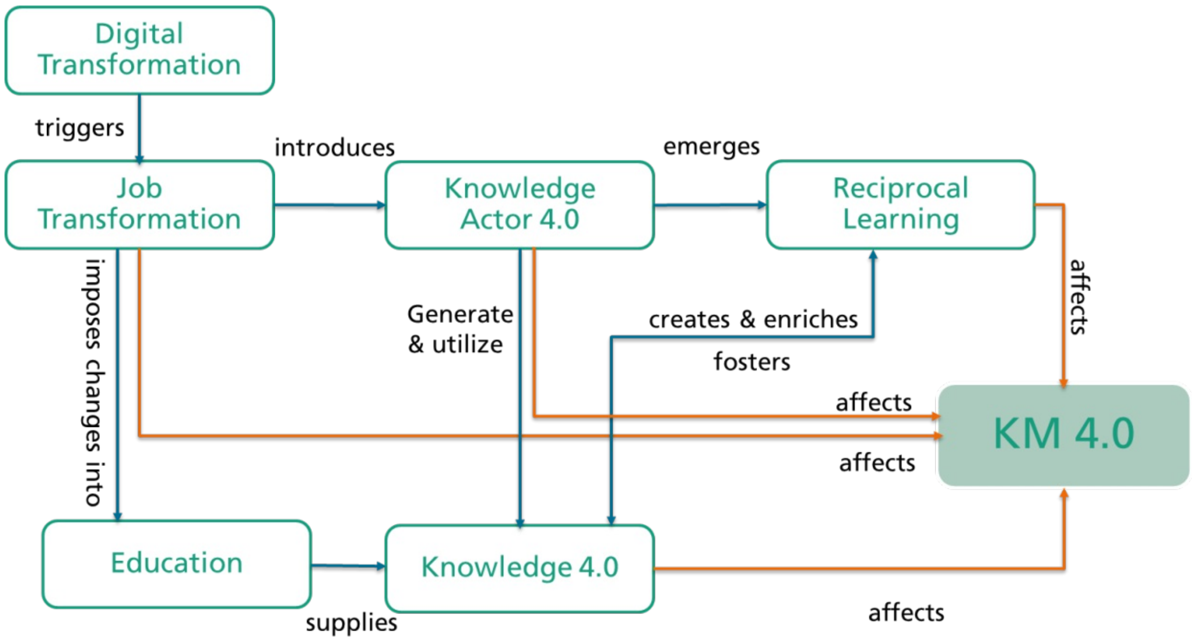

Figure 10. Factors potentially affecting implementation of KM 4.0

II) **Job-Knowledge-Education matches and mismatches** should be examined through systematic consideration of the emerging ontologies of Knowledge 4.0 and Knowledge Actors 4.0. The educational targets, types of education and learning materials should be reconsidered in relation to requirements for new jobs, demanded job-knowledge as well as human-machine hybrid workplace settings. Notably, the concept of learning factory helps to overcome mismatches.

III) **Reciprocal Learning and Mutual Dependencies between humans and machines in knowledge creation and utilization** require measures and tangible experimental analyses, which turn on the light into the direct/indirect relations between workforce productivity and learning effectiveness. In particular, it should be investigated whether the degree to which learning outcomes have been achieved correlates with productivity. This requires building a valid assessment model, which identifies all correlated factors and their degree of dependencies and significances.

IV) **Adaptive and Knowledge-Based Assistance Systems** should be established and implemented for managing collective intelligence of manufacturing enterprises. Human and machine DKPs, therefore, should be semantically represented with a functional linkage to the aforementioned model for assessing the correlation between productivity and learning effectiveness under various constraints in real-world manufacturing systems such as safety and data privacy as well as smart factory objectives such as variability and scalability of products, flexibility of processes and adaptivity to changes.

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Chapter 2: Knowledge-Based Maintenance

2.1 Transformation of Maintenance Strategies, Operation and Planning in Industry 4.0: Overview and Outlook

2.1.1 Rubik's Cube-Inspired Maintenance Problem-Solving

Solving a Rubik´s Cube seems always the same way. However, human brain may gain benefits more if it discovers how to solve the cube by recognizing patterns, improving spatial awareness and dexterity proactively, rather than learning by trial and error reactively. Solving maintenance problems is similar to a Rubik's Cube, while each cell of the cube is a data-driven, dynamic and changeable structural and functional unit, which can influence the problem-solving process (cf. Figure 11).

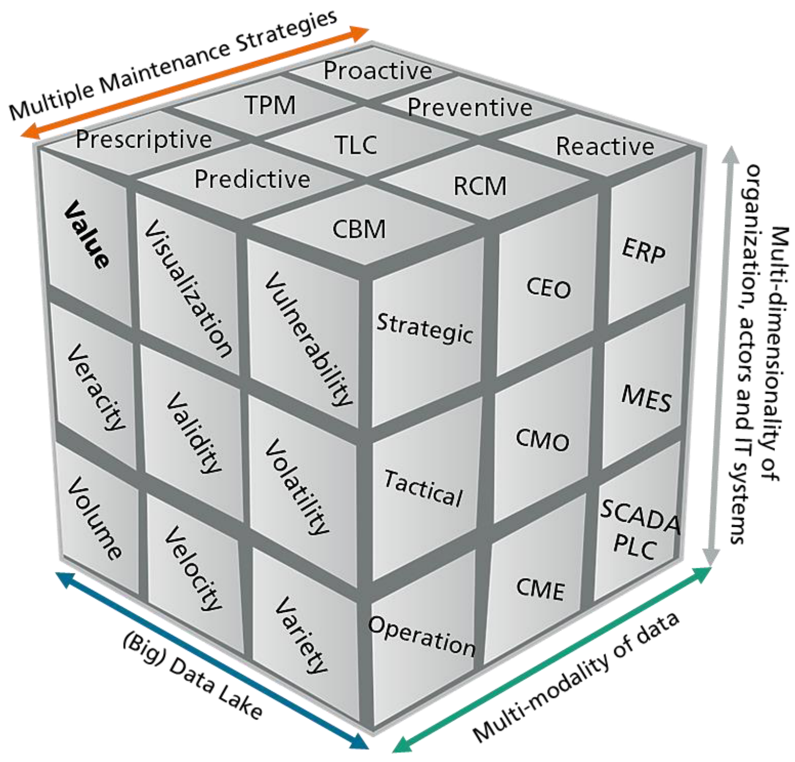

Figure 11. Maintenance Rubik's Cube – Reprinted from (Ansari & Glawar, 2018)

Reliable knowledge, enhanced logic skills and boosted problem identification and solving solutions are, therefore, required to take appropriate actions with respect to this multilateral complexity (cf. Figure 11). Solving maintenance problems deals with complexities due to (cf. (Ansari, Glawar & Nemeth, 2019)):

1) **Multi-dimensionality of maintenance organization, actors and IT systems:** A maintenance organization consists of operational, tactical and strategic levels, in which different actors ranging from operators, (chief maintenance) engineers, project managers; chief maintenance officer and top management, including production manager and CEO, play a certain role. In addition, maintenance IT-landscape consists of several systems, which provide data about machines, processes, resources (personnel, material, etc.), plans, quality control, costs as well as operational, tactical and strategic measures and key performance indicators (KPIs), such as overall equipment efficiency (OEE), availability, productivity, etc.
2) **Multiple Maintenance Strategies and approaches:** Maintenance strategies can be classified into three major groups as follows:
   - **Management strategies** like total productive maintenance (TPM), total lifecycle cost strategy (TLC) or reliability-centered maintenance (RCM), which provide certain recommendations and standard measures for goal-setting and proper definition and implementation of maintenance activities, including division of tasks, cost monitoring and controlling strategies, quality and performance management, organizational learning, documentation and content management, knowledge transfer, etc.
   - **Maintenance strategies and approaches without sensing and computing technologies**, which can be categorized into three approaches, namely:
     - *Reactive Maintenance* (Run-to-failure-strategy), which aims at low routine maintenance costs but may lead to high costs in case of equipment failure and increase risk of long downtimes.
     - *Preventive Maintenance*, which aims at planning and performing maintenance activities in regular intervals. Hence, time or a usage triggers are used to schedule maintenance. Preventive approaches results in reducing likelihood of failure, while an ongoing-effort is necessary.
     - *Proactive Maintenance*, which aims at determining the roots causes for machine failure through taking measures or corrective actions to avoid equipment failure altogether, e.g. give workers training on best-practice machine operation to be able to avoid reasons for equipment failure.

- **Maintenance strategies and approaches with sensing and computing technologies**, which can be categorized into three approaches:
  - *Condition-based Maintenance (CBM)*, in which maintenance is performed only when equipment problems have been registered by means of condition monitoring via sensors. Employing CBM approaches and technologies (Hand-held or mobile devices or retrofitted or integrated sensors) leads to identifying and resolving anomalies prior to functional failure.
  - *Predictive Maintenance*, which aims at enhancing CBM by means of On-Premise and/or Cloud-based analytic software and solutions (e.g. static rule-based analytics or dynamic model-based analytics), which allow making predictions on when equipment will fail and accordingly taking preventive actions timely.
  - *Prescriptive Maintenance*, which aims at recommending optimal maintenance measures and strategies for improving maintenance workflow and decision-making processes towards fully automated workflow management and self-healing.

3) **Multi-modality of data:** Linking single data elements collected, e.g. from machine's PLC or maintenance processes may provide independent information about different aspects of maintenance. For instance, while machine failure signal can reflect malfunction of one of its subsystem; it can also indicate inappropriate planning, which causes subsystem degradation and affects its remaining useful lifetime.

2.1.2 CRISP-DM Methodology for Discovering Knowledge from Big Data

The emergence of CPPS and (Industrial) Internet of Things (IoT) as well as data-driven technologies brings the attention of maintenance professionals to "Data", in particular "Big Data". From practical point of view, maintenance may gain benefits from using Big Data to boost the (business) value creation, especially for increasing the ability to predict and react to failure timely, appropriately and resource efficiently, decreasing maintenance costs, and most importantly retaining and increasing availability of facilities over time. As shown in Figure 12, generating competitive advantages (Business Values) from Big Data depends on several characteristics credited as 10Vs, Value plus 9Vs (cf. (Chen, Chiang & Storey, 2012; Tian, & Liu, 2017)), namely:

- *Volume* of data sources,
- *Velocity* of data flow (data generation, creation, refreshing, etc.),
- *Variety* of data structures such as log data, machine data, sensor data, audio, text, images, video files, web data, etc.,
- *Variability* of data with regard to inconsistencies in the data (anomalies or outliers), data dimensions (types and resources), or inconsistent speed on loading data into databases,
- *Veracity* i.e. reliability of the data source (in its context) and its meaningfulness to the purpose of analysis,
- *Validity* i.e. accuracy and correctness of the data for its intended use,
- *Vulnerability* dealing with sophisticated (cyber-)security and data privacy problems,
- *Volatility* referring to the rate of change in the values of stored data over a period of time (considered to be irrelevant, historic or not useful any longer), and last but not least
- *Visualization* of data which is challenging due to limitations of in-memory technology and poor scalability, functionality, response time, etc.

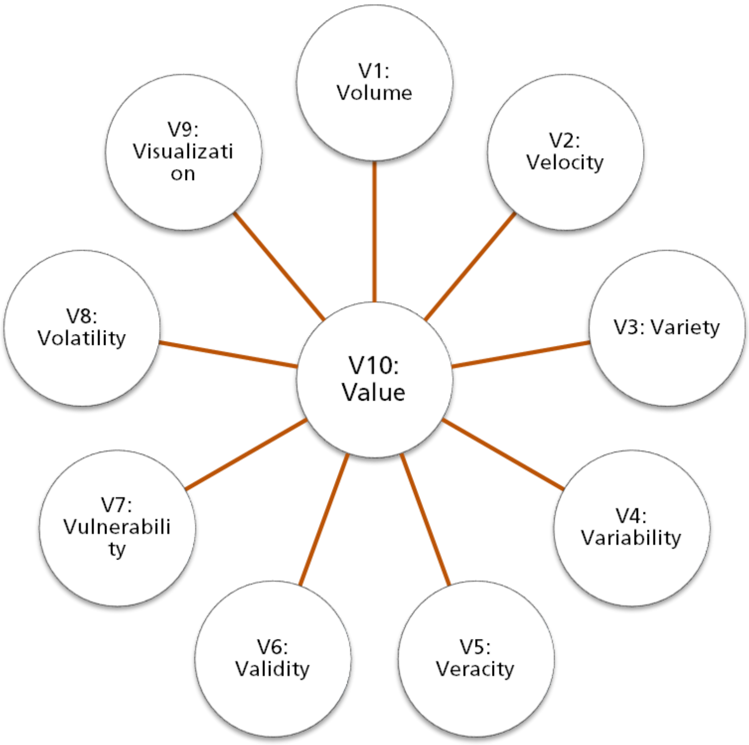

Figure 12. 10Vs for characterizing Big Data

Discovering knowledge from Big Data can be simply interpreted as building and learning a model, e.g. based on historical or real-time machine data, and exposing the model to new input data to make predictions. In other words, predictive data analytics refers to "building and using models that make predictions based on the patterns extracted from historical or real-time data" (Kelleher, et al., 2015). As depicted in Figure 13, The six key phases of a predictive data analytics project lifecycle are defined by the Cross Industry Standard Process for Data Mining (CRISP-DM) (Chapman, et al., 2000), namely i) potential analysis and business understanding, ii) data understanding, iii) data preparation and integration, iv) modeling and visualization, v) evaluation, and vi) deployment.

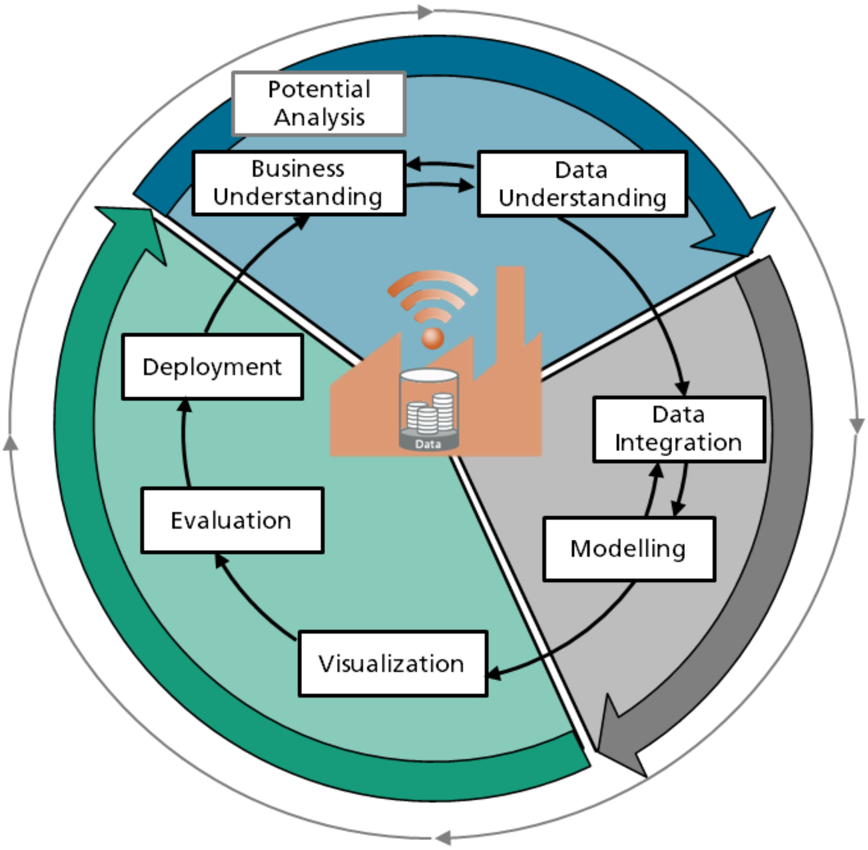

Figure 13. CRISP-DM – Adopted from (Chapman, et al., 2000)

The fourth phase, modeling, is where machine learning (ML) algorithms are employed to build prediction models (Kelleher, et al., 2015; Fürnkranz, et al., 2012). The best model which fits for the purpose of prediction, for instance down time prediction, will be evaluated and proved for deployment e.g. in manufacturing execution systems (MES). In particular, ML is "defined as an automated process that extracts patterns from given data" (Kelleher, et al., 2015). To this end, one may distinguish between two main approaches: 1) *Supervised ML* which "assumes that training examples are classified (labeled)", i.e. learning relationship between a set of descriptive features and a target feature, and 2) *Unsupervised ML* which "concerns the analysis of unclassified examples" (Kelleher, et al., 2015; Fürnkranz, et al., 2012).

Other types of ML include semi-supervised and reinforcement learning. Depending on the purpose of analysis and related parameters, four families of ML approaches are foreseeable namely, information-based, similarity-based, probability-based, and error-based learning (cf. Table 2).

Table 2. Four Main Families of ML Algorithms - Adopted from (Kelleher et al., 2015; Ansari, Erol & Sihn, 2018)

	Learning Approach	**Description**	**Example of algorithm**
Machine Learning Families	Information-based Learning	Employing concepts from information theory to build models.	Decision Trees
	Similarity-based Learning	Building a model based on comparing features of known and unknown objects, or measuring similarity between past and forthcoming occurrences.	k nearest neighbor (k-NN), Case-Based Learning
	Probability-based Learning	Building a model based on measuring how likely it is that some event will occur.	Dynamic Bayesian Network
	Error-based Learning	Building a model based on minimizing the total error through a set of training instances.	Multivariable linear regression

2.1.3 Evolution of Knowledge-Based Maintenance

Despite the massive technological enhancement and introducing sensory and data-driven systems in the age of Industry 4.0, maintenance management and organization still suffer several problems, which significantly affect value creation process, such as:

- Missing linkage of process, machine and environmental data
- Missing knowledge about influencing factors that lead to malfunctions of components
- Incomplete and redundant data acquisition that leads to limited and not significant data stocks
- Unexhausted data recording and analysis through condition monitoring due to the lack of operation and selection systematics
- An inaccurate prediction of moments when components fail leads to
    - Premature change of components or tools and hence underutilization
    - Delayed maintenance operations and thus to a variety of unscheduled downtimes

From the author’s point of view, data generation and collection in large scale, and applying data mining procedures are not only optimal ways towards achieving the ideal portrait of maintenance, characterized by optimal time to react, low costs and high availability. Therefore, certain aspects of CRISP-DM methodology should be further developed and integrated into maintenance processes, namely:

- identifying the purpose of analysis (competence question to be answered) tailored not only to availability but also to quality, consistency, validity, completeness and comprehensiveness of data,
- selecting and employing appropriate semantic modeling and analytical approaches, methods and tools, and
- linking explorative learning (of new knowledge) and exploitative learning (from prior knowledge, i.e. solution, cases, etc. stored in the maintenance knowledge-base).

Furthermore, the common ground for characterizing maintenance in the context of smart factories may refer to its organization's ability to:

- predict hidden patterns and events, i.e. *prediction capability*,
- optimize current and forthcoming plans, i.e. *optimization capability*,
- adapt with work-order changes and reconfigurations, i.e. *adaptation capability*,
- continuously learn from failure events and former decision-making instances, i.e. *learnability*,

  and finally

- (completely) automatize maintenance workflow and decision-support systems, i.e. *capability of intelligent actions and self-direction*.

Following this line of research, the term *"Knowledge-Based Maintenance" (KBM)* is introduced to denote the aforementioned functional capabilities and features. KBS overarches multiple maintenance concepts and approaches including descriptive, diagnostic, predictive and prescriptive maintenance in various maturity and complexity levels (cf. Figure 14).

The term KBM has been discussed in the literature of maintenance and assets management, where the main assumption is that competitive advantages for reducing maintenance cost are achieved through holistic consideration, rather than atomistic, of all influential components and gaining knowledge of maintenance (cf. (Sturm, 2001; Reiner, et al., 2005; Pawellek, 2013; Biedermann, 2014)). According to the conceptual model proposed by (Pawellek, 2013), KBM takes into account long-term effects of maintenance policies and decisions on economic terms, as a non-isolated sub-domain of production systems, which influences on organizational value creation. From this point of view, maintenance should be considered as a learnable organization (Biedermann, 2014). In the learnable organization, knowledge is created in different organizational levels (strategic, tactical and operational levels) through comprehensive consideration of maintenance consequences, system conditions, and processes (Pawellek, 2013). KBM collects machine (systems), process, and products data, which are then transmitted to three areas that provide overall strategies of maintenance, namely i) risk-based maintenance, ii) condition- or time-based maintenance, and iii) Total Productive Maintenance (TPM) and lean maintenance (Pawellek, 2013). KBM is responsible for unified consideration of outcomes collected from the three areas (Pawellek, 2013).

From critical point of view, although the aforementioned concept of KBM proposed by Pawellek (2013) is comprehensive, it only aims at establishing a linkage between multiple maintenance management strategies without indicating the logics of the relation, and the extent of deploying or producing knowledge. Moreover, i) methods for knowledge acquisition, modeling and representation, ii) the types, structures and heterogeneity of knowledge assets as well as iii) multi-dimensionality of maintenance organization, (knowledge) actors and IT systems have not been discussed.

Yet, several aspects of the KBM in relation to the Rubik's Cube (cf. Figure 11) have remained unexplored. Notably, the concept of KBM in the context of CPPS should integrate intelligent functions into maintenance processes and comply with knowledge-based methodologies (Russell & Norvig, 2016; Beierle & Kern-Isberner, 2014), which has not been exclusively considered in the literature of production and operation management.

Over the past years, the author has been striving to extend the definition of KBM particularly from the perspective of semantic modeling and representation as well as static rule-based or dynamic model-based analytics. The main goal is to enrich the KBM concept, underlying methodologies and procedures by introducing different instances of KBM in relation to their complexity and maturity levels and to achieve both holistic and atomistic consideration of all influential components for gaining and protecting the knowledge of maintenance (cf. Figure 14). As elaborated in (Ansari, Glawar & Nemeth, 2019), KBM is defined as "*a functional unit responsible to i) continuously support value generation and ii) facilitate developing and protecting maintenance collective knowledge across smart factories, which is enhanced by need- or* *opportunity-driven knowledge detection, discovery, modeling and representation approaches*". Hence, KBM may employ a variety of methods, depending on the intended purpose of modeling and analysis, including advanced statistics, stochastics, real-time computing[12] and analytics, ML algorithms, static rule-based or dynamic model-based analytics, and sematic modeling and representations. In the context of CPPS, KBM is demonstrated by its advanced functional capabilities, namely, knowledge discovery, prediction, optimization, adaptation, (self-)learning and ideally self-direction.

As depicted in Figure 14, the proposed concept of KBM is categorized into four instances depending on the maturity and complexity of its functional capabilities. Each type of KBM can answer a certain competence question as follows (cf. (Ansari, Glawar & Nemeth, 2019)):

- **Descriptive maintenance (Type I, Low Complexity, Low Maturity)** answers the question "What happened?" by providing information about previous maintenance operations. Thus, it supports information collection and analysis and increases the level of information visibility.

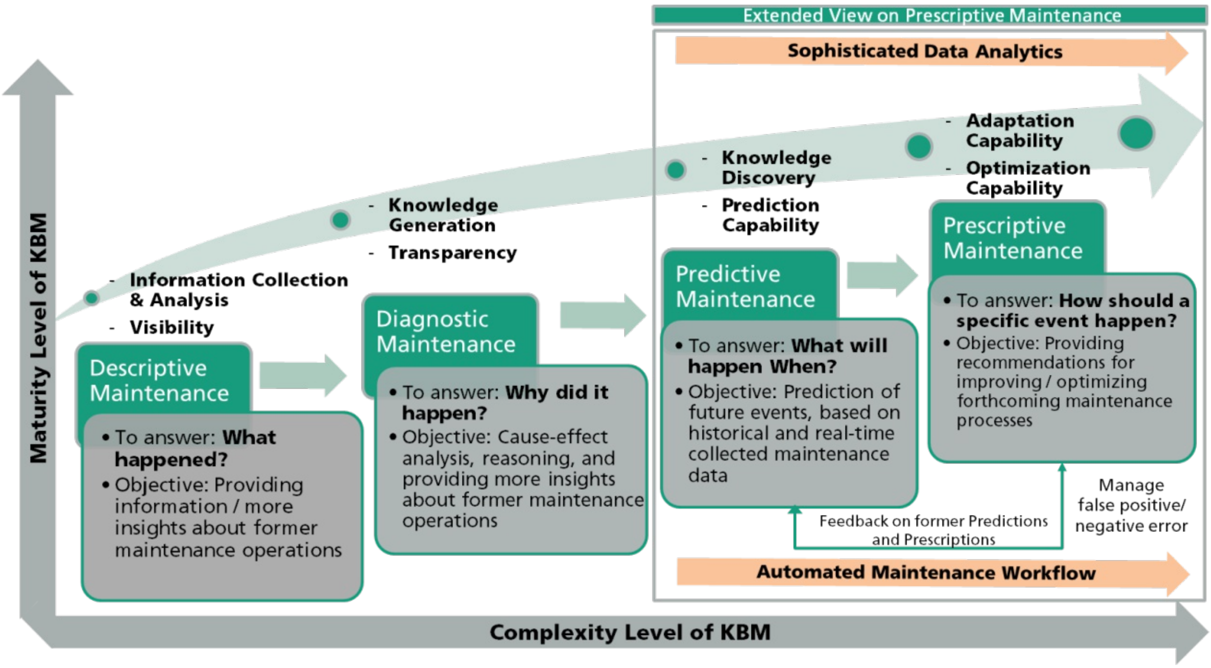

Figure 14. Evolution of KBM: Maturity & Complexity Levels – Reprinted from (Ansari, Glawar & Nemeth, 2019)

- **Diagnostic maintenance (Type II, Medium Complexity, Low Maturity)** answers the question "Why did it happen?" by analyzing cause-effect relations, reasoning, and

[12] Cf. (Lee, 2017)

providing further technical details about former maintenance operations. Therefore, it supports knowledge generation and increases the level of knowledge transparency.

- **Predictive maintenance (Type III, High Complexity, Medium Maturity)** answers the question "What will happen when?" by learning from historical maintenance data, possibly in real-time, and predicting future events. Thus, it supports knowledge discovery and enhances the level of (semi-)supervised or unsupervised prognostic capabilities. Notably, this is often referred to as "Smart Maintenance", "Data-Driven Maintenance" and "Maintenance 4.0", not only in scientific but also in commercial contexts.
- **Prescriptive maintenance (Type IV, High Complexity, High Maturity)** answers the question "How can we control the occurrence of a specific event?" (How should a specific event happen?) by providing actionable recommendations for decision-making and improving and/or optimizing forthcoming maintenance processes. It also refers to the recent advances in enhancing self-organization and self-direction capabilities of CPPS, which ideally aim at machine self-diagnosis and scheduled maintenance. Hence, prescriptive maintenance may reach the highest degree of maturity, which involves complex methods to produce and reinforce adaptation and optimization capabilities.

2.1.4 Outlook

Introducing the concept of KBM leads to consolidating several aspects of maintenance management, KM, data analytics and AI into a new research group at the TU Wien, namely "*Smart and Knowledge-Based Maintenance (SKBM)*", which aims to establish an interdisciplinary research portfolio and innovative model focusing on maintenance thinking, design and operation as a mediator between both academia and industry stakeholders. Figure 15 illustrates the overall portfolio of the SKBM.

Future research directions in SKBM are outlined by three Topic Areas (TAs) (cf. Figure 16), namely:

- TA-I - KBM focusing on application of AI and semantic technology in maintenance,
- TA-II - Human-centered CPPS and maintenance dealing with the emergence of human-machine knowledge actors in maintenance operation and planning, and
- TA-III - Future-oriented maintenance strategies and approaches.

In the TA-I, the main challenge is to establish prescriptive maintenance operation and planning, i.e. developing autonomous (self-learning and self-directing) maintenance workflow management and decision support and its integration into production control models. The meta-question here is "*Can a machine maintenance its health score?*".

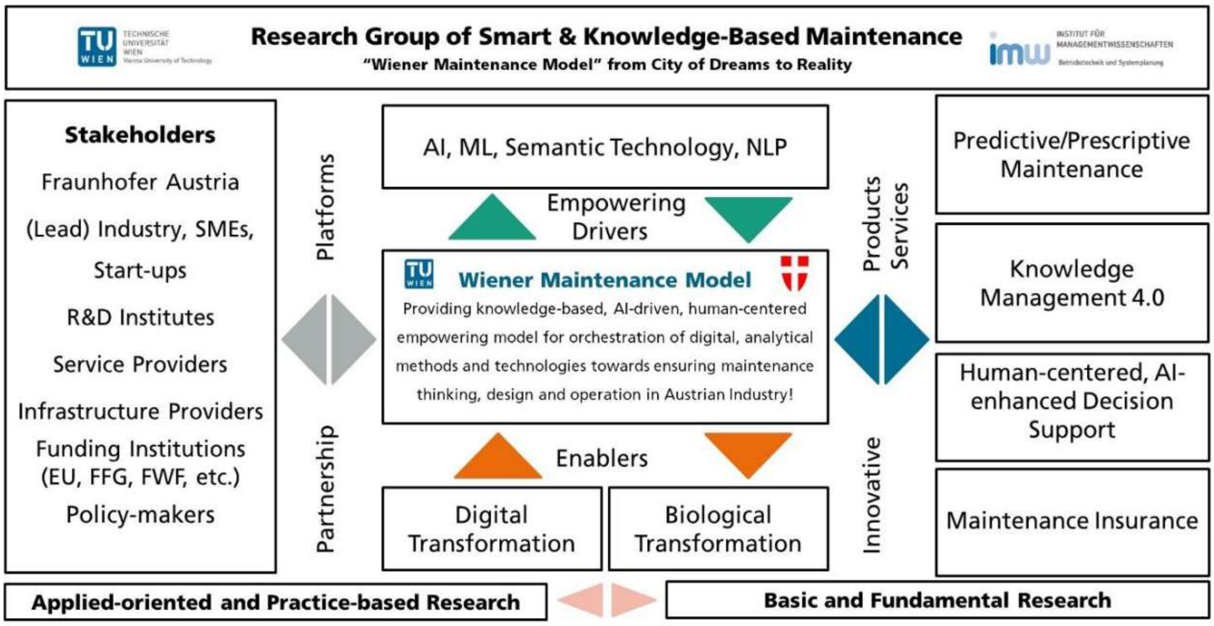

Figure 15. TU Wien's Research Group of Smart and Knowledge-Based Maintenance

In TA-II, the role of human and machine as a knowledge actor in maintenance (decision-making and problem-solving) processes is investigated (cf. (Ansari, Hold, & Sihn, 2018; Ansari et al., 2018b)), as extensively discussed in Chapter 1. The evolution of maintenance jobs (tasks) and jobholder profiles is examined considering new division of tasks between human and machine workforce and developing new learning strategies, models, approaches and novel didactical concepts for optimal collaboration of humans and machines (i.e. AI agents, cobots, etc.) on performing maintenance tasks. In particular, the focus is on modeling and measuring human-machine reciprocal learning (cf. (Ansari, Erol & Sihn, 2018)) in maintenance and identifying the impact of learning on labor and machine productivity (cf. (Ansari, et al., 2018a)).

In TA-III, novel concepts are investigated to provide new methods and tools for TA-I and TA-II. In particular, three sub-topics are foreseen:

- **Digital Twin for maintenance:** Integrating real-time data streams into simulation-based and digital models of machines for real-time (re-)configuration and online directing of machines, especially by focusing on automatic and agile ontology learning and (case-base) reasoning rather than relying on simulation-based models.
- **Maintenance Analytics with Strong Security:** Dealing with (cyber-)security, performing data analysis on encrypted data, and making analytics platform more secured and efficient e.g. by means of Blockchain. The goal is to provide a new Digital Twin for

remote monitoring and controlling platform and related business model for involving multiple stakeholders, namely original equipment manufacturers (OEMs), machine operators and suppliers as well as industrial insurance companies to predict and ensure moment of failure dynamically.

- **Biological transformation in maintenance:** Employing, adopting or developing biological and bio-inspired principles, functions, and approaches for KBM with the aim of achieving its full potential. This is inspired by the emerging subject area of Biological Transformation in Manufacturing (cf. (Byrne, et al., 2018)).

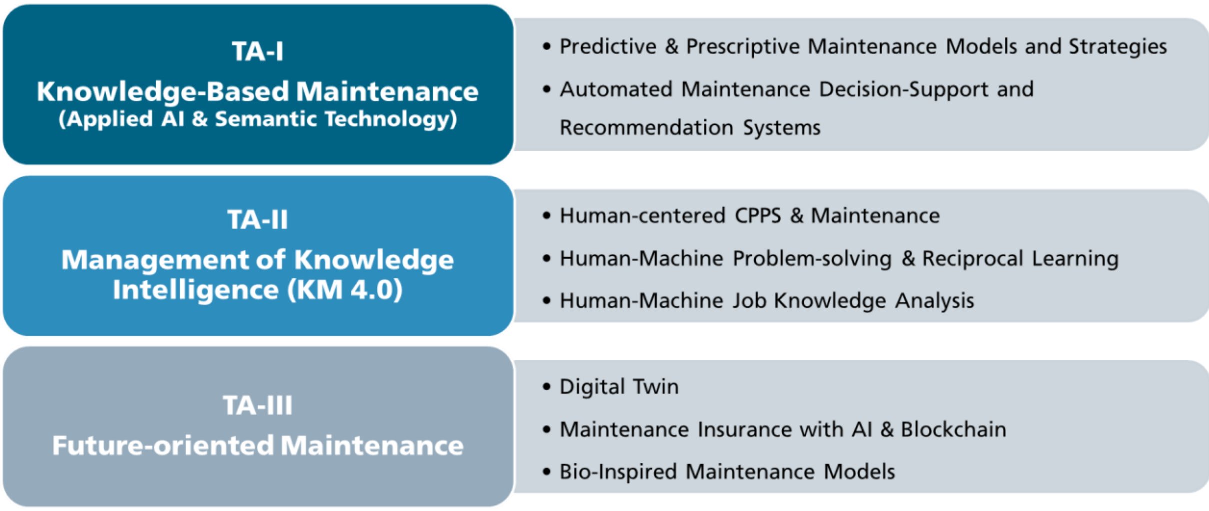

Figure 16. SKBM's Topic Areas for conducting research in Maintenance Management

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