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IFAC PapersOnLine 52-13 (2019) 1597–1602

Knowledge Management 4.0: Theoretical and Practical Considerations in Cyber Physical Production Systems

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Knowledge Management in the era of Industry 4.0 (KM 4.0) in both human- and technology-oriented perspectives is a strategic and operational function comprising exploration and exploitation processes. It is responsible to accomplish two major tasks. First, KM 4.0 should continuously support value generation through enhancing and balancing need- or opportunity-driven knowledge generation and knowledge utilization capacities. Second, KM 4.0 should persistently facilitate developing and protecting human-machine collective intelligence across manufacturing enterprises and in particular smart factories. Hence, KM 4.0 is an enabler to maximize competitive advantages and derive business values in the manufacturing enterprises. The revival of AI and emergence of autonomous and learnable technologies challenge the unique role of human as a knowledge actor, decision-maker, problem-solver and learner. What are the considerations on rethinking KM approaches in relation to the march of technological enhancements? This paper proposes a definition and discusses the theoretical foundation of KM 4.0 as well as related practical aspects that should be taken into consideration, especially in dynamic, data-driven and hybrid human-machine working environments in smart factories.

Keywords: Knowledge management in production; Industry 4.0; Decision-support for human operators; Smart manufacturing systems; Complex adaptive systems and emergent synthesis in manufacturing.

1. INTRODUCTION

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 in the light of enhancing sensing and computational technology, manufacturing industry is undergoing substantial changes and transformations.

Knowledge Management (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). In the age of rapid technological innovation and change, KM is a key enabler for value creation. 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 studied. The proliferation of digital technologies, emergence of human-centered cyber physical production systems (CPPS), autonomous, learnable and collaborative systems in smart factories and revival of AI raise undeniable questions about the theoretical foundation, i.e. ontological and epistemological aspects, of KM 4.0 (cf. (Porter & Heppelmann, 2014), (Schumacher et al., 2016) and (Davenport & Kirby, 2016)). However, the majority of studies in the context of Industry 4.0 explore four typical areas, namely i) methodology for knowledge discovery, i.e. how to acquire knowledge, ii) methods of supervised, semi-/unsupervised data mining and machine learning, i.e. which procedures are appropriate to precisely and accurately acquire knowledge, iii) sources of knowledge, i.e. which types of data can be collected by means of wireless- and sensory systems, and iv) data management platforms, i.e. how the scalable data in heterogeneous structures should be stored.

Yet, the emergence of “machine as a knowledge actor”, complementarity and reciprocity of human- and technology-oriented perspectives on KM 4.0 are least discussed (e.g. see (North & Maier, 2018)). The fundamental aspects of KM 4.0, therefore, has largely remained unexplored and even unnoticed within the production- and engineering management community.

In the previous papers, the author and his colleagues have examined the complementarity of human and CPPS in smart factories, i.e. autonomous and collaborative machines, robotic- and AI systems deployed in highly automated production systems (cf. (Ansari et al., 2018b)). In particular, the emphasis was and is still on answering the fundamental question of “Who does what, when and under which conditions?”, i.e. human guides machine and/or machine guides human on accomplishing a (shared) task. Since learning is at the heart of problem-solving and decision-making, in answer to the previous question the subsequent one has been emerged as follows: “Who learns (what) from whom?”, i.e. machine learns from human and/or vice versa (cf. (Ansari, Erol & Sihn, 2018) and (Ansari, et al., 2018a)). The theoretical findings and practical evidences (cf. (World Economic Forum, 2018)) of shifting the division of labor between human, machine and algorithms reveal the importance of reconsidering two theoretical aspects,

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10.1016/j.ifacol.2019.11.428

namely i) the definition of KM 4.0 and ii) definition, role, interdependency and reciprocity of knowledge actors covering knowledge-holders/-producers/-users and in fact knowledge receiver (learner) in smart factories. Focusing on digital transformation in manufacturing industries, this paper paves the rest of the way and explores the concept of KM 4.0 especially in dynamic, data-driven and hybrid human-machine working environments in smart factories. In particular, the paper is intended to answer the following key questions: (1) What is the definition of KM 4.0 considering strategic and operational aspects in the context of Industry 4.0? (2) What are the theoretical (ontological and epistemological) and practical considerations on rethinking KM approaches in relation to the march of technological enhancements?

The rest of this paper is structured as follows. Section 2 discusses the concept of KM 4.0 and proposes a definition for KM 4.0. Section 3 focuses on theoretical, practical and critical considerations with regard to KM 4.0. Finally, Section 4 concludes the discussion of KM 4.0 by providing the pathways for further research.

2. KNOWLEDGE MANAGEMENT 4.0

2.1 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 and 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) and (Piñol et al., 2017). The former identifies four necessary competence categories namely, technical, methodological, social and 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*" (North & Maier, 2018) 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*" (North & Maier, 2018) 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).

2.2 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.

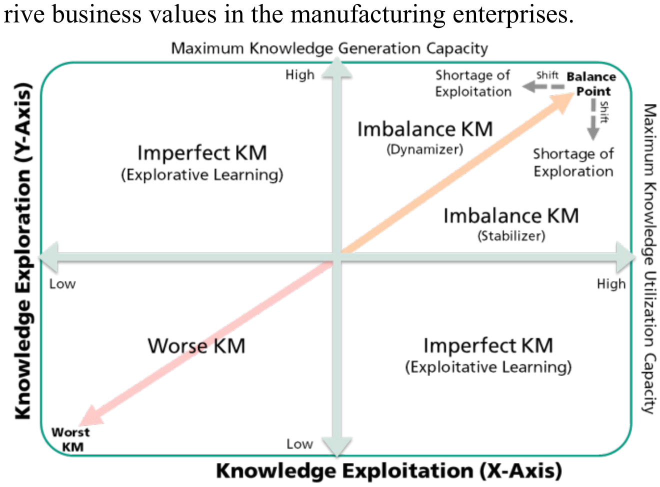

Fig. 1. Portfolio Matrix for KM 4.0

Figure 1 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.

3. THEORETICAL & PRACTICAL CONSIDERTATIONS

3.1 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.

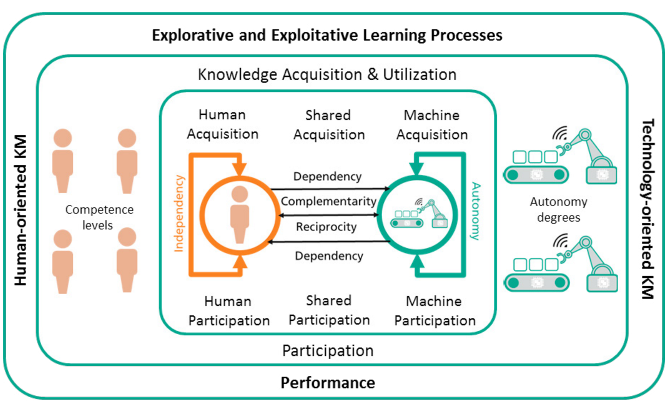

Fig. 2. Boundary System for KM 4.0

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 related instances, namely k-holder (for explicating and storing knowledge), k-producer (for completing existing knowledge and creating new knowledge), k-user (for transforming knowledge to skills and testing knowledge in practice, e.g. by on-the-job training), k-receiver (for selecting and accepting knowledge before stored by k-holder) and finally k-eraser (for unlearning knowledge, cf. Section 3.3). 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? Figure 2 depicts the boundary system for KM 4.0. 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 and consequently defines new relation and exchange modes, namely reciprocity.

3.2 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 2). 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, and

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. 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.

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 (humans-are-better-at)-MABA(machines-are-better-at) originally introduced by (Fitts, 1951). 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.

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) and (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)).

Focusing on the complementarity of the knowledge actors, Figure 3 depicts the meta-model for representing the concept of "Knowledge Actor 4.0" and related instances, namely human and machine.

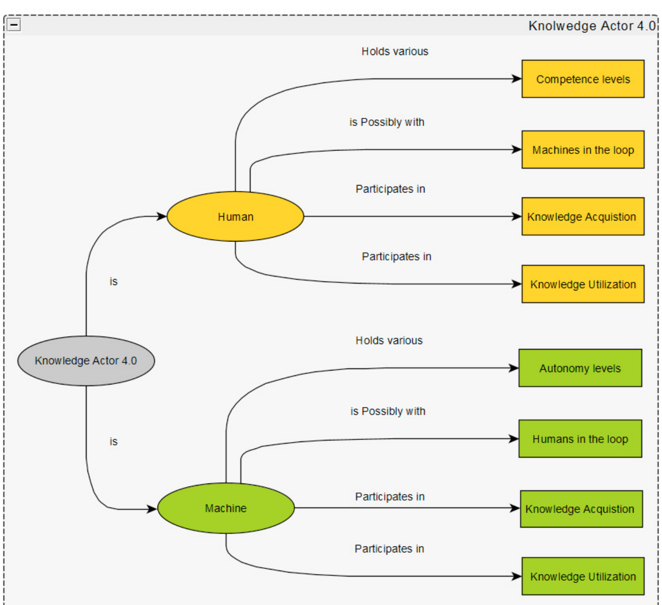

Fig. 3. Meta-model for representing the concept of Knowledge Actor 4.0

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. Figure 4 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 $KSAC_{ik}$ as in

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

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

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

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:

$$Sim\left(\overrightarrow{dkp}_{Demand}, \overrightarrow{dkp}_{Supply}\right) = \frac{\overrightarrow{dkp}_{Demand} \cdot \overrightarrow{dkp}_{Supply}}{|\overrightarrow{dkp}_{Demand}| \cdot |\overrightarrow{dkp}_{Supply}|}$$

$$= \frac{\sum_{k=0}^{t} KSAC_{ik} \times KSAC_{jk}}{\sqrt{\sum_{k=0}^{t}(KSAC_{ik})^2} \cdot \sqrt{\sum_{k=0}^{t}(KSAC_{jk})^2}} \quad (3)$$

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.

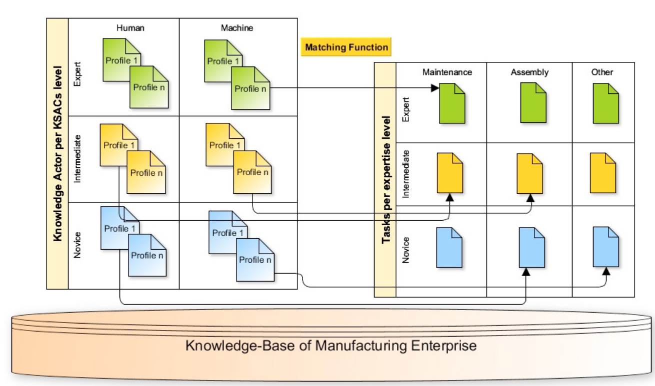

Fig. 4. Knowledge Base of a Smart Factory

3.3 Practical Considerations

The following example illustrates how the previously mentioned matching function (cf. Section 3.2) 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 5 and 6, 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 $\overrightarrow{dkp}_{Demand} = (0.6, 0.7, 0.8)$, (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.

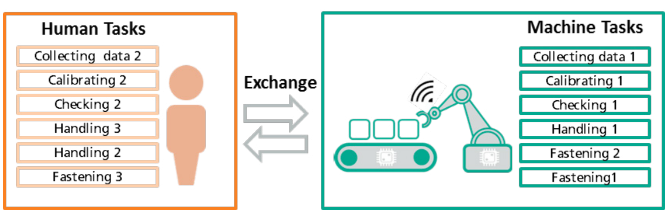

Fig. 5. Assigning distinct tasks to Knowledge Actors 4.0

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.

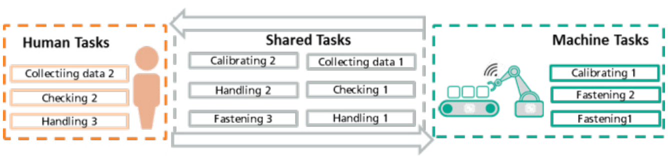

Fig. 6. Assigning shared tasks to Knowledge Actors 4.0

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.

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.

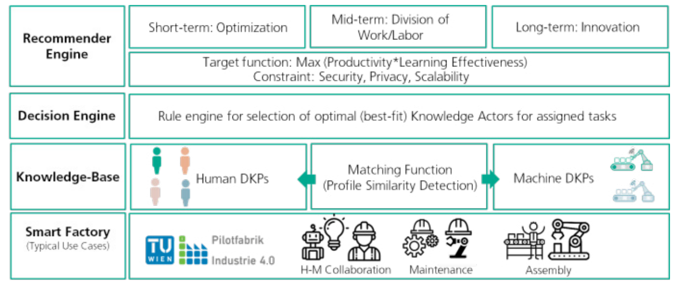

Fig. 7. A Knowledge-Based Assistance System for selection of best-fit Knowledge Actor 4.0 – Adopted from (Ansari, et al., 2018a)

3.3 *Critical Consideration: Learning vs. Unlearning of Knowledge*

Looking again at the portfolio matrix for KM 4.0 (cf. Figure 1); 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 1, 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, relearning 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.

4. CONCLUSION & OUTLOOK

This paper discusses KM 4.0, especially focusing on the effect of Industry 4.0 and undergoing changes in manufacturing enterprises on KM. Figure 8 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.

II) Job-Knowledge-Education matches and mismatches should be examined through systematic consideration of the emerging taxonomies 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.

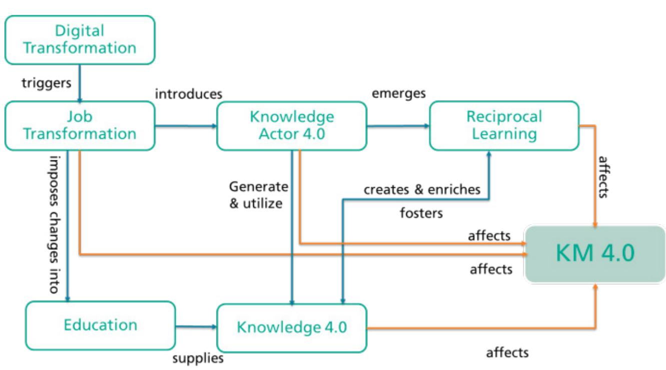

Fig. 8. Factors potentially affecting implementation of KM 4.0

The above listed directions define the pathways for further investigations on KM 4.0 in future.

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