A Conceptual Model of Knowledge Dynamics in the Industry 4.0 Smart Grid Scenario

Abstract

Technological advancements are giving rise to the fourth industrial revolution - Industry 4.0 - characterized by the mass employment of smart objects in networked big data environments. Enabled by cyber-physical capabilities, Industry 4.0 vision describes a realization of highly reconfigurable, self-organizing, decentralized, thoroughly connected, and resilient industrial product-service systems. The purpose of this paper is to propose a theory-based knowledge dynamics model in the smart grid scenario that would provide a holistic view on the novel, knowledge-based interactions among smart objects, humans, and other actors as an underlying mechanism of value co-creation in Industry 4.0. An integrated, multi-loop and three-layer - physical, virtual, and interface - model of knowledge dynamics in smart grid scenario is developed by building on the concept of *ba* – an enabling space for interactions among actors and the emergence of knowledge. The model depicts how big data analytics are just one component in unlocking the value of big data, whereas the tacit engagement of humans-in-the-loop – their sense-making and decision-making – is needed for *ba* to be activated, insights to be evoked from big data analytics reports, and individual customer needs to be met.

Keywords: Industry 4.0, tacit knowledge, humans-in-the-loop, big data analytics, internet of things and services, smart grid

Paper type: Conceptual paper

1. Introduction: The emergence of Industry 4.0

The fourth industrial revolution, commonly termed as Industry 4.0, is currently taking place. Since the beginning of industrialization, technological advances have led to transformations that are termed as industrial revolutions (see Figure 1). The first three were termed as industrial revolutions *ex-post* and were characterized predominantly by mechanization, electrification, and division of labor, and widespread digitalization (Hermann et al., 2016; Lasi et al., 2014). In contrast to the first three, this one was established *ex-ante* and is characterized by a range of new technologies that are converging the physical, digital and biological worlds and radically impacting all industries and economies, even challenging how humans work and relate to each other (Schwab, 2017). The term "Industry 4.0" originates from Germany where it became publicly more known with a strategic initiative called "Industrie 4.0" and becoming a part of "High-Tech Strategy 2020 for Germany" (Kagermann et al., 2011). The growing interest in Industry 4.0 is evidenced by numerous research and strategic initiatives proposed by the main industrial countries, which aim to develop more intelligent and sustainable industrial systems. China announced its research initiative "Made in China 2025" while the USA has its initiative "Industrial Internet". Other terms that attempt to describe the new industrial transformation are "smart industry", "integrated industry" or "smart manufacturing" (Hermann et al., 2016).

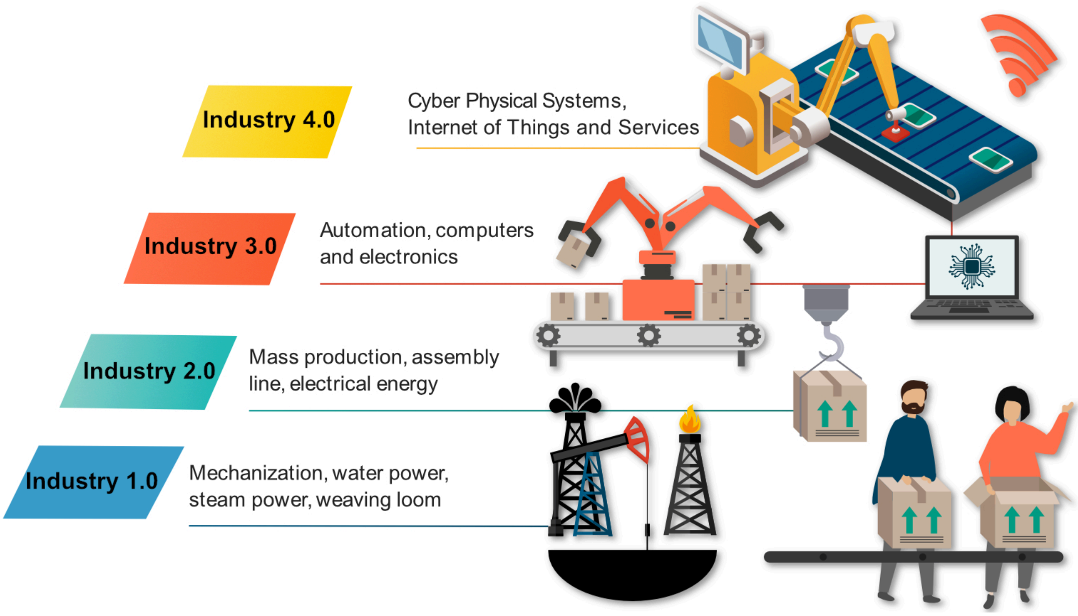

Figure 1. Industrial revolutions

Industry 4.0 scenarios are characterized by the mass deployment of smart objects (SOs), such as smart machines, smart meters, home appliances, and electric vehicles. The foundation of SOs and an "enabling technology" of Industry 4.0 are cyber-physical systems (CPS). CPS are not a new technology by themselves, but rather a convergence of several emergent technologies such as the Internet of Things, Internet of Services, Multi-Agent Systems, Service-oriented Architectures, Augmented Reality, Machine-to-Machine, and ubiquitous availability of computing, communication, and storage (Leitao et al., 2016). They are characterized by the cyber-physical formulation of their systems, that is, the symbiosis between their physical function and the abstract representation of this function which is a machine-readable description in the virtual space (Monostori, 2014; Leitao, 2016).

Industry 4.0 provides several application fields: smart production, smart grid, smart logistics, and smart healthcare (Leitao et al., 2016). Our knowledge dynamics exploration in Industry 4.0 is informed by the industrial smart grid (SG) scenario (Greer et al., 2014). The foundation of SG is a strong coupling of digital technologies with the physical energy domain, particularly via mass deployment of SOs, that is, networked embedded devices such as smart meters, home appliances, and electric vehicles. Networking is achieved by using SOs and decentralized energy management systems to coordinate the individual components. This means that not only energy but also data is transported in SG, so that network participants receive information on energy production and consumption at short intervals.

Thus, increasing use of networked SOs results in the continual generation of high volumes and heterogeneous data types coming from multiple sources, i.e. big data (Alahakoon and Yu, 2016; Lee et al., 2015). In SG scenario, smart meters capture data with big data characteristics, for instance, massive amounts of fine-grained energy consumption data which enable many potential opportunities for generating value from such data, such as for decision-making and planning processes (Alahakoon and Yu, 2016). Being agents with embedded computation and physical processes, SOs have a role not only in capturing data through sensors but as well managing and learning from big data and acting upon the environment using actuators (Lee et al., 2015). As a particular characteristic of Industry 4.0, advanced big data mining algorithms are integrated within SOs at dispersed parts of the system, facilitating distributed big data analytics (Leitao et al., 2016). This enables SOs to perform complex autonomous acts, that is, to control their internal states and behavior, and to realize self-x properties such as self-learning or self-healing, in other words, autonomous, self-organizing machine intelligence (Gronau, 2016; Gronau et al., 2016; Leitao et al., 2016). Due to the application logic that SOs carry, real-time decision making based on big data can be done by SOs in an automated manner. Enabled by the CPS capabilities, Industry 4.0 vision describes a realization of highly reconfigurable, self-organizing, decentralized, thoroughly connected, and resilient industrial systems (Alahakoon and Yu, 2016; Gronau, 2016; Kagermann et al., 2013; Lee et. al, 2016; Leitao et al., 2016). Artificial intelligence-enabled automation has been proclaimed as a backbone of the fourth industrial revolution by World Economic Forum (Schwab, 2016). The shift towards always-responsive and situated service provisioning is as well brought to the table by a huge amount of fine-grained data, collected, stored, and analyzed by SOs. Industry 4.0 enables the creation of individualized, "batch size one" products and individual customer needs to be met (Lasi et al., 2014; Miorandi et al., 2012; Monostori, 2014).

The deployment of SOs in Industry 4.0, hence, has not only a technical but also a social dimension regarding humans who interact with them and use their services (Oks et al., 2017). In this sense, Industry 4.0 marks a shift toward service transformation in the big data environment, that is, a shift toward CPS-based Product-Service Systems with humans as active participants (Kagermann et al., 2013; Lee et al., 2014; Lee et al. 2016, Leitao et al, 2016). However, some limitations could be observed in research concerning this socio-technical aspect of Industry 4.0. The role of humans-in-the-loop and their knowledge as a part of value co-creation in new industrial ecosystems has so far not been sufficiently considered (cf. Leitao et al., 2016). Furthermore, we have failed to identify an integrated framework that would involve knowledge-based activities of both machine and human actors. Taking these issues into consideration raises the following research question:

RQ: What is the role of human and machine knowledge, and their interactions, in unlocking the value of Industry 4.0 SG scenario?

In this conceptual paper, we attempt to address this question by developing a model that would provide a holistic view on knowledge dynamics as an enabler of value co-creation in Industry 4.0 smart grid (SG) scenario. Our working definition of knowledge dynamics is that of interdependent knowledge-based activities performed by the multiplicity of actors of the socio-technical world – including SOs, computational entities, and human actors – which lead to value co-creation. In Industry 4.0 CPS-based product-service systems, the target of value co-creation is not a product offering, but a collaborative product-service solution that can satisfy customers' needs (Lee et al., 2014).

The paper is structured as follows. We start by covering the research context and methodology (sec. 2) and follow by critically examining and clarifying the terms data, information, human and machine knowledge (sec. 3.1 and 3.2). Furthermore, we discuss issues of modeling knowledge dynamics (sec. 3.3). Afterwards, we provide an overview of knowledge dynamics in SG scenario (sec. 4). By analyzing current literature, we extract components of SG ecosystem which we then apply in the conceptual model (sec. 4.1) and describe its operational mechanism as an enabler of the value ecosystem that it creates (sec. 4.2). The paper proceeds with a discussion (sec. 5), implications of the proposed model (sec. 6), limitations and future research (sec 7) and a conclusion (sec. 8).

2. Research context and methodology

A thorough review of the KM literature revealed that a holistic model regarding knowledge dynamics in Industry 4.0 scenarios does not exist yet. To be specific, we have used a combination of keywords, such as Industry 4.0, industrial internet, big data, internet of things, internet of services, big data analytics, to review the articles in Journal of Knowledge Management, VINE Journal of Information and Knowledge Management Systems, Knowledge Management Research and Practice, and Journal of Information and Knowledge management. Among the total of 67 papers that we have found, only one paper addresses Industry 4.0, a research contribution carried out by Wilkesmann and Wilkesmann (2018) in VINE. The authors investigated how different ways of organizing human work in Industry 4.0 digitalized environment may lead either to the reproduction of routines or to innovations. However, the focus of the study was on enhancing the understanding of the potential that Industry 4.0 environment provides, and to review some current implementations, and not on the nature of human and machine knowledge-based interactions as enablers of value co-creation in Industry 4.0. There are a number of papers covering big data, big data analytics, Internet of Things and related research topics (e.g. Lugmayr et al., 2017; Pauleen and Wang, 2017; Sumbal et al., 2017), which allowed us to enhance our understanding of important questions and themes. In a recent paper on the interrelationship between big data and KM, Sumbal et al. (2017) underscored that human tacit knowledge is necessary to better understand, test, confirm or reject the results obtained through big data analytics. Lugmayr et al. (2017) introduce the term

Cognitive Big Data to stress the socio-technicality of knowledge systems, to show the interdependency of the computational systems and the human mind, and to emphasize the need of big data research that would focus on assisting humans in their cognitive efforts. This research provided relevant hints on the nature of the relationship between the machine and human knowledge, however, since, similar to Sumbal et al. (2017), it does not address Industry 4.0 scenarios, it provides only limited directions for knowledge dynamics in Industry 4.0, the focus of our study. Addressing the identified need, in this paper, we attempt to build a coherent model of knowledge dynamics in the Industry 4.0 SG scenario.

Specifically, to address our research question, first, we draw upon relevant KM theories, foremost on Polanyi`s, common (albeit often misinterpreted) reference point for his successors, in an attempt to seek answers to epistemologically fundamental questions such as: *What is the nature of knowledge? What is the difference between human and machine knowledge?* We attempt to do so since we believe that "questions of method are secondary to questions of paradigm, which we define as the basic belief system or worldview that guides the investigator, not only in choices of the method but in ontologically and epistemologically fundamental ways" (Guba and Lincoln, 1994, p. 105). It is our contention that the view on the nature of knowledge needs to be explicated since this epistemological disposition will guide the understanding of the important questions pertaining to the modeling of knowledge dynamics. The particular value of our model then lies in explicating theoretical assumptions underlying the nature of knowledge and considering the consequences of these assumptions on the knowledge dynamics modeling in Industry 4.0 SG scenario. The argument put in this paper is that missing from dominant models of knowledge dynamics was the recognition that human tacit knowledge cannot be converted or operationalized due to its emergent properties (see Sec. 3.3. for further discussion). Following this logic, as we will detail later, our main conceptual move in building knowledge dynamics was to adopt the concept of *ba* (Nonaka and Konno, 1998), since it allowed us to account for the emergent nature of knowledge-based interactions.

Second, to understand knowledge dynamics in Industry 4.0 we reviewed a variety of science and technology studies in journals on industrial and systems engineering, manufacturing, computer science, and networks, with a particular focus on the topic of the use of knowledge in smart grids (cf. Alahakoon and Yu, 2016) and in new industrial systems more generally (cf. Lee et al., 2015; Leitao et al, 2016). Our investigation revealed that existing contributions only partially analyze human-machine knowledge-based interactions. Integration of these various theoretical strands, however, provided a substantial basis for our understanding of knowledge dynamics in Industry 4.0. To be specific, based on the critical analysis of literature in a broad range of fields covering Industry 4.0 and KM, and on a combination of those viewpoints, we have conceptualized main components relevant for the implementation of SG scenario and their relations and operationalized them into the coherent three-layer and multi-loop knowledge dynamics model. Then, we illustrated the application of the model through the human-to-machine interaction via a user interface in the SG scenario.

3. Conceptual foundations: nature of knowledge and the concept of *ba*

3.1. Duality of knowledge

It has been more than 50 years since Polanyi (1966), the scientist and philosopher, provided a foundational theory where he was pondering knowledge in terms of the duality, that is, tacit and explicit knowledge as being indivisible and mutually constituted. Such, constructivist rationale, is in mere contrast to the positivist rationale and its foundational assumption of the tacit-explicit dualism - that knowledge can be deconstructed into discrete units with an implication that knowledge is an artifact that people or machines can possess (e.g. Kogut and Zander, 1992). The implication of the constructivist assumption of the duality, on contrary, is that knowledge is embodied (i.e. it doesn`t exist outside the knower), socially constructed (i.e. it is co-created by the human individual and social sensemaking), tied to a practice (i.e. it is inseparable from the interactions), and culturally embedded (i.e. it is shaped by the sociocultural context in which interactions occur) (e.g. Brown and Duguid, 1991; Hislop, 2002).

By following researchers who criticize the positivists` stance for neglecting inarticulable personal, social, and cultural aspects of knowledge and over-emphasizing the technological matters (e.g. Hislop, 2002; Tsoukas, 2005), we base our understanding of knowledge on the constructivist rationale, particularly on Polanyi`s (1966) theory. To illustrate the essence of this view on knowledge, let us imagine a prosumer in an SG scenario, where, due to the adoption of renewable generation and microgrids, millions of prosumers both produce and consume energy in their homes and businesses. This leads to the creation of energy markets where prosumers need to optimize both their production and consumption to maximize their profits through their local trading decisions in a real-time (see Sec 4.2.3 for further discussion).

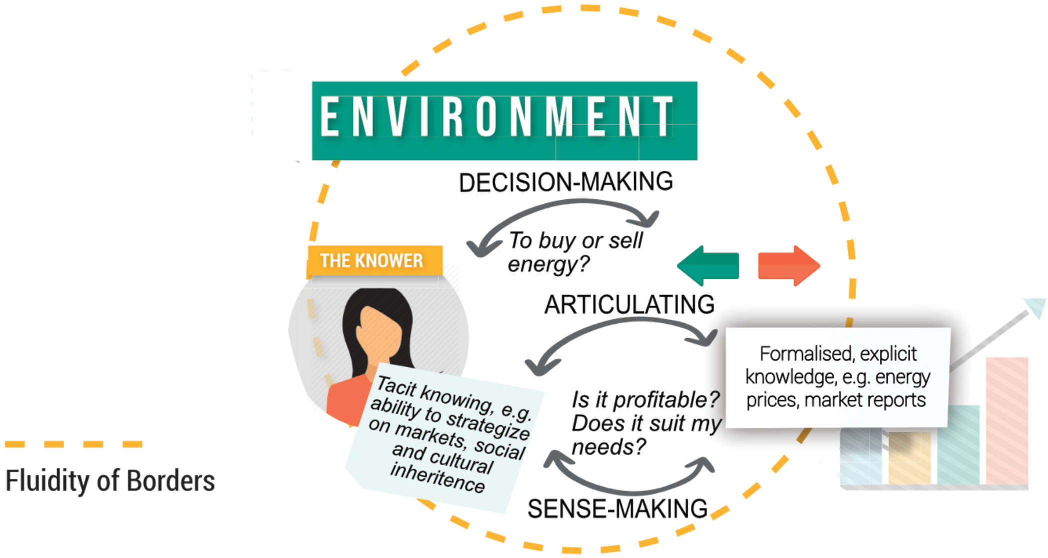

Figure 2. Dynamic relations that comprise human knowing

We assume a context where a prosumer receives information about a trading situation via user interface (UI) embedded in a smartphone- such as energy prices and forecasts about the consumption or production on the market, makes sense out of it and decides how to act upon it – whether to sell the energy (generated or stored earlier) or to buy energy (either for consumption or storage). Prosumer has the skill to trade the energy, that is to say, her tacit knowledge enables her to perform the action of trading energy – she *knows* trading strategies and rules of the game governing the speculations on the market. However, the prosumer is only aware on a subsidiary level of such knowledge – *she knows more than she can tell* (Polanyi, 1966). The object of her focal awareness, the focal target, is the market speculation itself. An attempt to focus on the trading ability or how to interact with the UI, for example, would make her "performance clumsy to the point of paralyzing it" (Tsoukas, 2005, p. 6), that is, such focus would deprive these tacit components of meaning (Polanyi and Prosch, 1977). Instead of attending to the tacit components, the knower – in order for her action to be effective in a real-time – only subsidiarily relies on them (attends *from* them) and switches her focal attention (attends *to*) something else – effective market speculation (Polanyi, 1966; Tsoukas, 2005).

Since the integration of the subsidiaries to the focal target relies on the internal tacit act, tacit knowledge is inherently inarticulable (Polanyi and Prosch, 1977). What occurs as a result of an attempt of articulation is a new artifact, which is mutually constitutive with the tacit background but is not articulated tacit knowledge *per se*. As Polanyi (1966, p. 20) elaborates, even what is often considered to be the detached, objective knowledge, such as the information about the prices of the energy or market dynamics forecasts received via UI, "can be only constructed by relying on prior tacit knowing and can function as a theory only within an act of tacit knowing".

Thus, in the case of our prosumer, the sense she will make of energy prices and market dynamics forecasts will vary from other prosumers depending on her tacit knowledge, which includes, among others, personal needs, values, beliefs, know-how, and emotions. The prosumer decision making, regarding, for example, buying or selling energy, would as well depend on the same factors. Equally, sense-making of different reports will depend on the context of a knowledgeable audience, that is, the reports will be "read" differently in the household or business context, and differently "read" by every individual depending on her or his tacit knowledge (Stenmark, 2002). It could be, therefore, more fruitful to focus on "knowing" activity, which is about relations and interactions, rather than on "knowledge" as an object, which is about possession.

Polanyi argued that the tacit and focal terms cannot be conceived separately from articulate and explicit, and insisted on overcoming well-established dichotomies such as objective vs. personal. Nevertheless, we believe it is useful to keep some of these terms conceptually distinct to facilitate the analysis. As depicted in Figure 2, tacit and explicit components are presented separately but we use the double-headed arrow to indicate the duality (i.e. mutual constitutiveness of tacit and explicit) inherent to human knowledge-based (knowing) activities such as sense-making, articulating, and decision making.

3.2. Machine and human knowledge

In KM literature, when discussing the relationship between knowledge and technology, one important point of discussion is whether human knowledge can be formally described so that a digital machine can handle it. Positivists would argue that human knowledge can be objectified and codified, and would seek to utilize technology for handling a representational understanding of knowledge. Constructivists, on the contrary, would argue that human knowledge cannot be separated from the knower and that what can be found outside in a formalized, explicit form is merely data and information (Stenmark, 2002). However, the answer to whether a machine can generate knowledge and act intelligently, it is our contention, depends on how machine knowledge and intelligence are understood. While arguing that tacit components of knowing, since inherently inarticulable, remain beyond calculative rationality that computers can simulate, we believe that it is beneficial to use the term machine knowledge and related concepts such as artificial intelligence and machine learning. In this sense, machines can convey data and information, but they cannot "be said to communicate an understanding of themselves" (Polanyi, 1958, p. 21), which remains under the domain of tacit knowing. Thus, only by "virtue of this act of comprehension, of this tacit contribution of [her] own, can the receiving person be said to acquire knowledge" (Polanyi, 1958, p. 22).

We follow Ackoff (1989) to define data as symbols representing objects and events. Big data, then, comprises data sets of enormous size and complexity, having characteristics such as volume, variety, velocity, and veracity, signifying magnitude of data, structural heterogeneity, the rate at which data are generated, and unreliability of data, respectively (Gandomi and Haider, 2015). We consider as useful to differentiate data and information in terms of their functional differences (rather than structural); thus, one way is to perceive information as data that is processed into a usable form (Ackoff, 1989). We further understand the application of big data analytics and artificial intelligence fields as a way of achieving higher-level "learning capabilities" of machines, used to identify non-obvious, hidden relationships and patterns in big data (Sumbal, 2017). Whereas what constitutes machine knowledge, then, inevitably alters with technological advancements, the essence remains: it is based on the logic that can be specified and, thus, automated (Ackoff, 1989). To put these thoughts into the context of Industry 4.0 and CPS, it is worthwhile to note that the old "expert system" and rule-based approach to artificial intelligence is nowadays complemented with more complex statistical processes. In the Industry 4.0 environment, SOs are capable of learning, adjusting and acting in the environment. Advances in machine learning include deep learning techniques which exploit multilayered neural networks that aim to mimic the thought and decision-making process of humans (cf. Lee et al., 2016; Sonntag et al., 2017). Still, humans handle resulting machine-generated data and information independently. They make sense of these results in their unique way, creating connections through the tacit acts, and subsequently, make decisions. At the same time, the complexity of human context, its personal, social and cultural dimensions, is hard to detect and interpret in machine`s terms; big data and subsequent analytics reports (articulate, explicit artifacts) lose meaning and value without context that needs to be brought to bear in order to adequately disambiguate them (cf. Boyd and Crawford, 2012). In Table 1 we provide an overview of the definitions, properties, and activities related to machine and human knowledge.

Table 1. Machine and human knowledge: definitions, properties, and activities

	MACHINE DOMAIN (DATA SPACE)			**HUMAN DOMAIN (EXPERIENCE SPACE)**
	DATA	**INFORMATION**	**MACHINE KNOWLEDGE AND INTELLIGENCE**	**TACIT KNOWING**
Definition	**Data:** Symbols that represent properties of objects, events **Big data:** Large volumes of diverse types of data generated at frequent intervals	Descriptions, processed data into usable form	Ability to apply algorithms, learn, and predict	The act of relating, dynamic capability
Knowledge-based activities	Big data sensing (*based on predefined data-structure embedded in the sensor*)	Big data management *(processing, integration, and aggregation of data to create information)*	Big data analytics (*modeling and analysis*; *including the application of artificial intelligence fields such as supervised and unsupervised machine learning*; *deep learning*)	Dialoguing with data, sense-making, and decision-making (*involving personal needs, beliefs, values, know-how, and emotions*)
Properties	Based on the logic that can be automated			Emergent

Further consequential argument adopted by constructivists is that data and information processed by machines require tacit knowledge not only to be understood but as well to be created. That is, there is neither “raw data” nor “isolated pieces of simple facts”; data emerge as a result of a pre-defined data structure, which defines the meaning of the phenomena sensed from the environment (Tuomi, 1999). Since the instrument used to collect data determines meaning relations that define what data is, the term “raw data” is an oxymoron (cf. Gitelman, 2013).

By perceiving its potential value in enabling real-time and evidence-based decision making based on real-time or “active” data, organizations seek to find processes to turn these increasingly large volumes of diverse types of data generated at frequent intervals, that is, big data, into meaningful insights (Gandomi and Haider, 2015; Lee et al, 2016). Particularly in the marketing realm, driven by the positivist rationale, the assumption is often made that big data analytical tools and artificial intelligence are capable of extracting “actionable insights”. However, since the “act of personal insight” is inherent in the act of tacit knowing (Tsoukas, 2005), the active involvement of humans is still required. Automated big data analytics make sense and unveil hidden patterns by applying algorithms to the “data space” (Lugmayr et al., 2017). Nevertheless, whereas they are the first stage in unlocking the value of big data, humans still need to make sense of reports (new data and information) and make their own decisions accordingly. This might involve critically testing assumptions, tracing backward the analysis, and discarding some aspects of the data and focusing on others, further data gathering and analyzing to justify initial insights (Labrinidis and Jagadish, 2012).

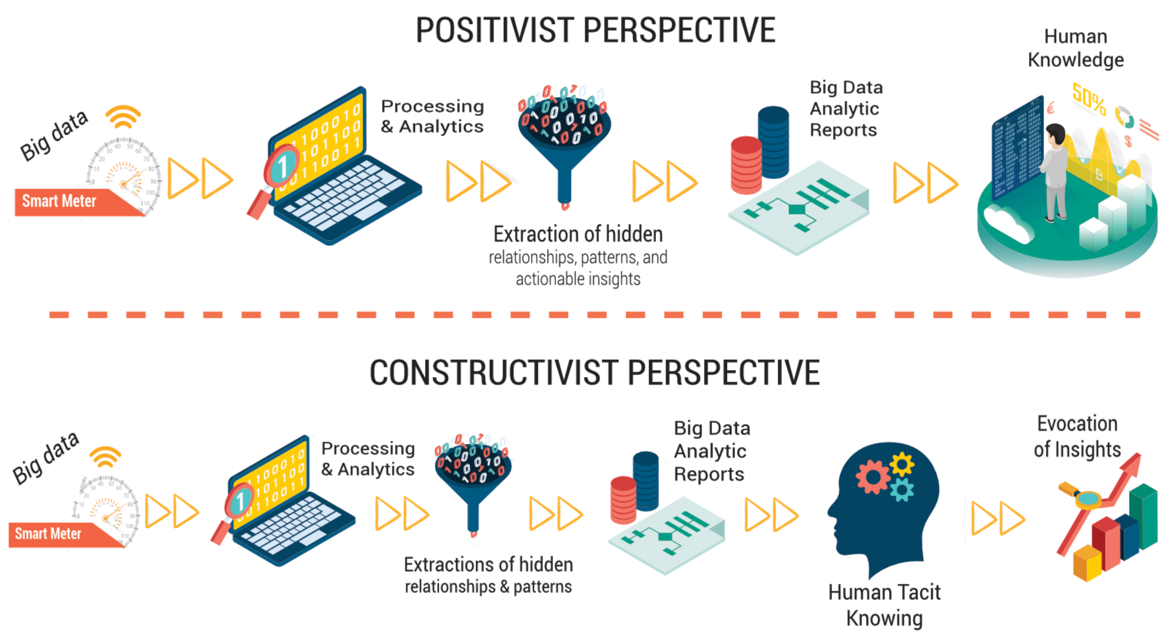

Figure 3. Differences in perceptions how insights are gained in “big data environment” according to the positivist and constructivist perspective

Insights, then, emerge as a result of the sense-makers` engagement with the data and will vary depending on the sense-makers' tacit knowing, that is, on the inarticulable internal tacit act which makes connections with personal needs, beliefs, values, know-how, and emotions, rooted in what Lugmayr et al. (2017) call "experience space". This is "a process of dialogue rather than one of discovery"; insights can only be "evoked by the data" but cannot be "explained from the data" (Bryant and Raja, 2014). That is, insights emerge from data, but cannot be revealed by the data itself: they are the result of the synergy of big data, analytic tools, and human tacit knowing (cf. Sumbal, 2017), a synergy where intuition leads synthesis of isolated bits of data and experience into an integrated, emergent picture that is more than sum of parts and results in an "aha!" experience (see Figure 3).

3.3. Modeling knowledge dynamics

Models of knowledge dynamics that are largely rooted in the positivistic logic, however, have limitations in representing the tacit, emergent properties of knowledge. As emphasized by Bratianu (2016), they are based on the two metaphors: *knowledge as a flow* (e.g. Nissen, 2002), which focuses on how knowledge moves through organizations and *knowledge as a process* (e.g. Gronau et al., 2016), which focuses on knowledge conversions between tacit and explicit knowledge. Such conceptualizations lead to two major limitations. First, the knowledge dynamics models based on the metaphor of *knowledge as a flow* do not account for the "forces which generate and control the knowledge flow" (Bratianu, 2016, p. 325). They do not acknowledge that all articulated content exists only in relation to an unarticulated tacit background. Second, conversions of tacit knowledge into explicit knowledge, implied by the knowledge dynamics model based on the metaphor *knowledge as a process*, reflect the dualistic view on knowledge, as discussed earlier.[1]

[1] Polanyi`s notion of duality of knowledge was often misinterpreted by his successors, most notably Nonaka and Takeuchi (1995). In their knowledge creation theory, they posited that knowledge is explicit and tacit along a continuum (cf. Nonaka and Von Krogh, 2009) and that tacit knowledge can be converted – to some degree - to explicit knowledge, that is, that it can be articulated in a form of concepts, models, hypotheses, metaphors, and analogies. However, such a view of tacit knowledge is not congruent with Polanyi`s, who perceived tacit as indivisible and essentially unspecifiable part of all knowledge. Later, Nonaka and Konno (1998, p. 40) offered a more holistic approach to knowledge by utilizing the Japanese

Knowledge dynamics models rooted in constructivist epistemology is in need of a conceptualization that more closely reflects the original intentions of Polanyi regarding tacit and explicit as inseparably related, as well as the emergent nature of knowledge-based interactions. That is, since it is not possible to completely specify in advance what kind of knowledge (also when and where) is going to be needed and relevant (Tsoukas, 1996, p. 11), the interactions are "always richer than any formal representation of it" (Tsoukas, 1996, p. 18). Putting the matter in those terms implies that knowledge dynamics models – instead of attempting to formalize, operationalize, or convert tacit knowledge – must turn to the human interaction as a primal source of knowledge emergence (Kakihara and Sørensen, 2002). In particular, to understand knowledge dynamics, we need to be attentive equally to the articulated content (data and information) provided by technical entities, to interaction through which the emergent tacit components get engaged, and to the space-time locationality in which this interaction occurs. It is the position resting on a view of knowledge as duality - and emergent properties of such duality - that provides the substantive basis for our knowledge dynamics modeling.

In KM tradition, the most influential account of dynamic properties of knowledge creation was provided by Nonaka and Konno`s (1998, p. 40) concept of *ba* as a "shared space for emerging relationships." *Ba* is grounded in the view that organizations are not merely an information processing machine, but an "entity that creates knowledge through action and interaction" (Nonaka et al., 2000, p. 6). Since it accounts for the inherent relational aspects of knowledge, it appears that there is a solid foundation to associate the concept of *ba* to Polanyi`s notion of duality of knowledge, particularly when the aim is to depict knowledge interactions or dynamics (cf. Grant, 2007). [2]

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concept of *ba*, that is, "a shared space for emerging relationships", however, by that time the tacit-explicit dichotomy already became part of the conventional understanding of knowledge among knowledge management theoreticians and practitioners.

[2] Nonaka and Konno distinguished four types of *ba* (i.e. originating, interacting, internalizing, and connecting) that correspond to the four conversions between explicit and tacit knowledge (i.e. explicit to tacit, tacit to tacit, tacit to explicit, explicit to explicit). Since this line of thought has a rationale in knowledge conversions which we, as stated previously, object, at least in this present study, we don`t attempt to go further into adapting the framework consisting of 4 types of *ba* to Polanyi`s notion of duality and including it into the knowledge dynamics modeling.

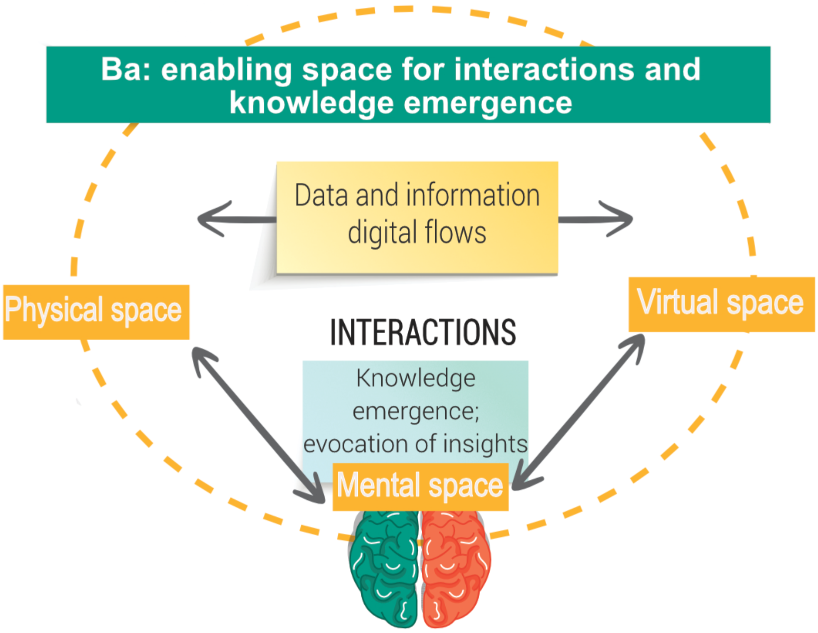

Figure 4. *Ba*: A relational space for emergent interactions through physical, virtual, and mental space

We understand *ba* as an enabling space for interactions and knowledge emergence, which requires human contribution (tacit knowing). Specifically, we perceive three mutually related accounts of *ba.* The first addresses the obvious*: ba* is a location where knowledge-based interactions take place, which involves mental (e.g. values, emotions, beliefs, needs), virtual (e.g. networks), and physical (e.g. factory, smart home) components. Moreover, *ba* unifies these components "in order to profit from the 'magic syntheses` of rationality and intuition" (Nonaka and Konno, 1998, p. 41). The second sense denotes *ba* as an existential space, a "shared context in motion" (Nonaka and Toyama, 2003, p. 8) in which human actors engage their tacit knowing (through time and space-sensitive, always unique configurations of interactions (Nonaka and Toyama, 2003). This sense of *ba* puts into focus that human engagement, their tacit knowing, is required to evoke insights and create meanings out of data and information provided by, for example, big data analytics reports. As Nonaka and Konno (1998, p. 41) emphasized, "If knowledge is separated from *ba*, it turns into information, which can then be communicated independently from *ba*. Information resides in media and networks. It is tangible. In contrast, knowledge resides in *ba*. It is intangible". The third account of *ba* implies an enabling context or enabling conditions for actors` interactions and knowledge creation (cf. Wei Choo and Correa Drummond de Alvarenga Neto, 2010).

In Industry 4.0 big data analytics are applied with an aim to address Industry 4.0 specific challenges and to unlock the value of big data. However, by using *ba* as a building block in knowledge dynamics modeling, as we will describe in the following sections in more details, we argue that big data and information can be analyzed automatically and can flow digitally through the virtual and physical space, while insights emerge only through the human tacit involvement in the mental space (as illustrated in Figure 4).

4. A conceptual model of knowledge dynamics in Industry 4.0 smart grid scenario

4.1. Model components

SG scenario offers a vision of smart energy systems in which energy producers, energy facilities, smart grid management, and energy customers are networked with one another in an evolving complex system of systems. Hermann et al. (2016) provide a useful basis for developing utilized constructs for the holistic conceptual model of knowledge dynamics. They identify components for implementation of Industry 4.0 smart manufactory scenario. We adopt their framework by reviewing the current literature on SG and identifying industry-specific components. Overall, we identify four main components: *Smart objects*, *Smart grid*, *Cloud-based Internet of Things and Services*, and *Humans in-the-loop.* As a critical difference to Hermann et al. (2016), we involve *Humans in-the-loop* as an independent component.

4.1.1. Smart objects

Large-scale deployment of SOs, such as smart meters (SMs) and smart substations, enable frequent capture of new types of data, for instance, fine-grained consumption, generation, power quality and event data (e.g. meter status) (Alahakoon & Yu, 2016). In addition to common big data characteristics, due to, for example, variable customers' demands and highly variable nature of renewables such as wind and solar, such data become variable, that is, variate in flow rates (Alahakoon & Yu, 2016). Cyber-physical fusion enables SOs to not only provide acquired data but as well to consume data, which enhances their own functionalities and increases data and information exchanged through the whole ecosystem. In this way, by complementing their functionalities with more powerful ones operating in the cloud, even resource-constrained objects of the physical world situated on the "edge" of the system such as home appliances become digitally accessible and manageable (Karnouskos, 2014).

4.1.2. Cloud-based Internet of Things and Services

SOs interact with each other or with humans through the "self-configuring, adaptive, complex network" of the Internet of Things (Minerva et al. 2015 p. 74). Coupling Internet of Things with Internet of Services, that is, ability of service providers to offer their services via internet (Hermann et al., 2016), the shift is occurring from IoT as a network that connects end-user devices to Internet of Things and Services (IoT&S) as a network that connects physical objects and humans - customers and providers - in order to offer a service. Increasing utilization of cloud computing paradigm in which services such as computation, storage, and network are offered on demand over the internet - leads towards the cloud-based IoT&S, enhances cloud-centric interactions, and brings even more flexibility and connectivity into industrial systems (Karnouskos, 2014; Meloni et al., 2018). The cloud-based IoT&S combines the capabilities of both cloud and edge computing and uses virtualization technologies to handle data from the underlying physical objects (Meloni et al., 2018).

4.1.3. Smart grid

The foundation of SG is a strong coupling of IoT&S with the energy domain, particularly via mass deployment of SOs. SG is a "power network" that integrates the "behaviors and actions of all stakeholders connected to it" with a goal to "efficiently deliver sustainable, economic, and secure electricity supplies" (Alahakoon and Yu, 2016, p. 1). In contrast to traditional power grids, which are characterized by unidirectional flows of electricity, SG is characterized by real-time bi-directional energy and information flows among participating actors, SM utility (e.g. smart home), and provider utilities (Greer et al 2014). The key building block of SG is the AMI and SMs deployed at end-user points, which enable innovative demand-response and demand-side management mechanisms which are seen as key for achieving a balance of supply and demand (Karnouskos, 2014). In SG, energy can be generated from distributed renewable sources and autonomous microgrids - customers become prosumers who generate energy by using small-scale generation infrastructures such as solar panels and feed energy that exceeds personal demand into the grid.

4.1.4. *Humans-in-the-loop*

According to Greer et al. (2014), humans make decisions within the seven SG ecosystem domains: bulk generation, transmission, distribution, customers, service providers, operations, and markets. Key stakeholders in SG make management decisions, regarding, for example, energy trading, managing customer relationships, grid optimization, or energy management. The customer is the stakeholder who consumes the energy, the stakeholder that the entire grid was created to support. SG ecosystem is characterized by the process of democratizing access to data, that is, opening data to various stakeholders via diverse web-based or mobile applications, which provides more possibilities for their increased and more meaningful engagement.

4.2. Operational mechanism

The SG scenario components identified in Sec. 4.1 form the basis of the model. Information about the domains comes from Greer et al. (2014). We define actors as entities that perform knowledge-based activities, including human actors, SOs and computational systems. Figure 5 illustrates how interaction among actors – humans in the mental layer, SOs in the physical layer, and computational systems embedded in the virtual layer – enables data and information flows in the physical and virtual layer and the emergence of new knowledge or insights in the mental layer.

Conceptual models are simplified representations of target systems. Hence, in the mental layer, we consider only the Human-to-Machine (H2M) interaction through UI and not the Human-to-Human (H2H) interaction. Since the mental layer is essentially an interface space for H2M interaction, we call it *an interface layer*. Furthermore, in giving examples of interactivity, in the following paragraphs, we focus on the demand response and demand-side management activities, aiming to keep supply and demand in balance, and on the role of the prosumer.

Whereas SOs and computational entities embedded in the cloud perform knowledge-based activities according to their application logic and received communication input (a code), by acknowledging the duality of knowledge and building on the concept of *ba* (Nonaka and Konno, 1998), here we consider human tacit knowing in the interface layer as a precondition for insights to be evoked from big data reports. In this way, value co-creation enabled by the symbiosis of the physical-virtual-interface layer is not occurring as much in a pre-given three-dimensional space itself as it is in a "topological space the network of interactions recursively create" as a whole (Kakihara and Sørensen, 2002, p. 8).

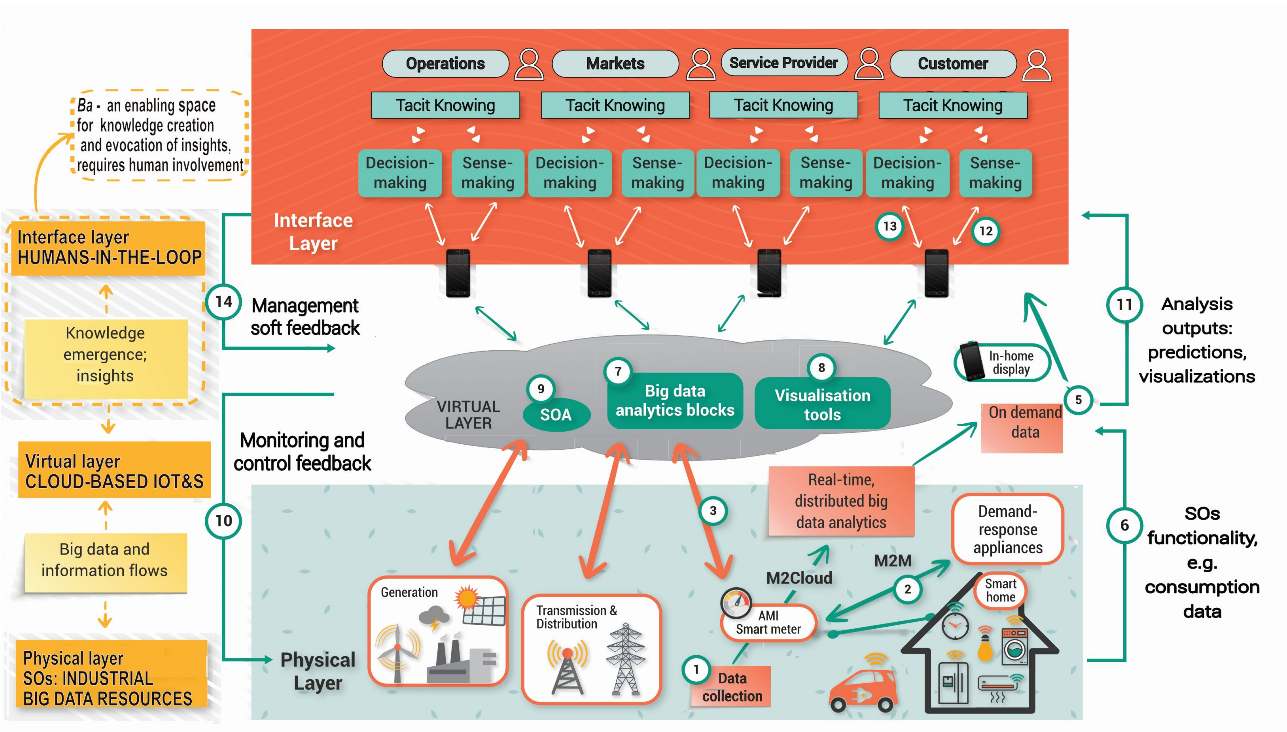

Figure 5. An integrated three-layer (physical, virtual, and interface) and multi-loop model of knowledge dynamics in SG scenario

4.2.1. Physical layer

SMs and other machine actors collect contextual consumption data for the entire smart home (1). They share data and information bi-directionally both in a machine-to-machine (M2M) manner (2) and via Cloud-based auxiliary services in a machine-to-cloud (M2Cloud) manner (3). Smart, distributed big data analytics for achieving self-organizing machine intelligence are used at the individual machine and fleet levels (13). Since being actuators, SMs can control and manage the energy consumption of smart appliances such as air-conditioner and refrigerators. Data that they capture locally is processed in real-time (4). Data analytics activities initiated by AMI are mostly data-driven, e.g. cluster analysis, which utilizes consumption data to generate consumption patterns and to identify typical customer behavior, that is, load profiles (Alahakoon and Yu, 2016). Deep learning techniques are used for modeling highly nonlinear relationships between the electricity consumption data provided by

SMs at different hours and on different days and the socio-demographic information of the customer to improve the accuracy of load profiles (Wang et al., 2018). SMs can provide their functionality, e.g. consumption data, as a service in a standalone mode; these data can on demand (5) be displayed to the customers via in-home displays, that is, interfaces for smart meter-to-customer and smart meter to service provider utility interactions. SMs, furthermore, encapsulate their functionality – in a form of data and information flows – to the cloud for further processing (6).

4.2.2. Virtual Layer

Virtual layer, that is, cloud-based IoT&S (the cloud) comprises of actors - computational entities - such as big data analytics blocks (7), visualization tools (8), and an integrated service-oriented architecture (SOA) (9). The cloud collects, stores, and analyzes massive amounts of data and information originating from SOs in the physical layer (6), and human-related data and information originating from the interface layer (14). The big data analytics blocks - due to high computational ability – analyze data in an aggregated form or by combining diverse types of data in a timely manner. Visualization tools generate customized statistical reports (e.g. load profiles) that are sent to humans in the interface layer who access the reports (i.e. new data and information) via various mobile and web-based applications. The cloud integrates the physical and interface layer via data and information based feedback loops.

In the cloud, application-driven activities such as decision trees and neural networks are triggered based on aggregated data about stakeholders needs, business needs, government policies, social and environmental factors (Alahakoon and Yu, 2016). For example, fine-grained system-wide consumption data can be merged with business data in the cloud for the purpose of setting up sophisticated demand-side management activities. Integration of SOs with service-oriented architecture (SOA) principles allows their dynamic behavior adaption based on the data feedback they receive from the cloud. For example, in response to particular conditions such as high pricing and peak periods, the bidirectional interaction between SMs and the cloud allows remote shifting of the time of use of home devices. Specifically, when wide-system demand is at peak period, the cloud can send an instruction to SOs in the physical layer to switch off individual appliances. This enables control of demand at different points in the system and ensures that demand is able to follow the supply of energy.

4.2.3. Interface layer

Interface layer constitutes humans-in-the-loop who interact with SOs through user UI that are integrated into third-party applications, mobile apps, and in-home displays. UI denote a contact point between the human and machine actors; it is at UI that the interactions between humans and SOs take place and a human dialogue (involving tacit knowing) with data and information occurs. These interactions occur either through direct interaction with SM, such as in the case of when customers receive SM generated data and information via in-home displays or via third-party applications mediated by the cloud. To be specific, as represented in Figure 6, humans-in-the-loop make sense (1) of incoming data and information provided by reports via UI, make decisions and implement them (e.g. regarding consumption management or energy trade) (2) and input their decisions via UI in a form of new data and information that are sent to the cloud and SOs for processing adjustment (e.g. SMs) (cf. Wiig, 2003). Rather than static, this is a dynamic, evolving process embedded in feedback loops (Forrester, 1958). These activities are governed by their tacit knowledge (3); it is only through the involvement of human tacit components that insights can be evoked and decisions reflecting inarticulable needs can be made.

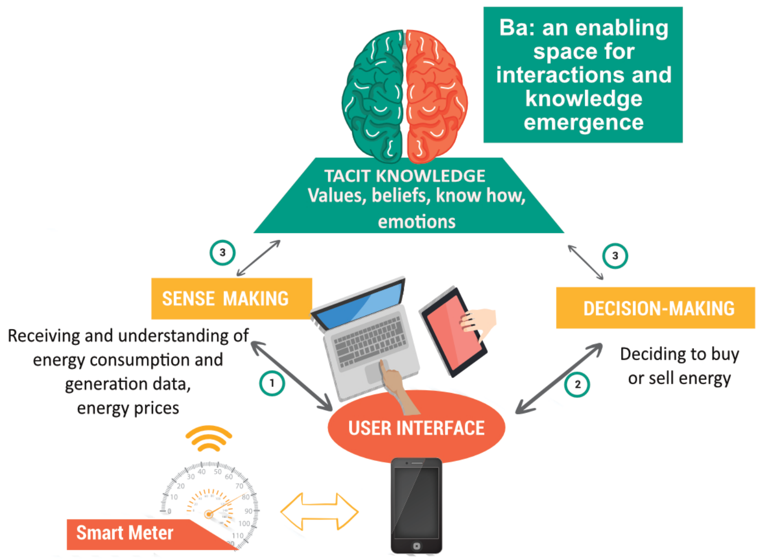

Figure 6. Human-in-the-loop (prosumer) knowledge-based activities via user interfaces

Let us extend the example of a prosumer speculating on the market to illustrate the point (see Sec. 3.1). Consider a household where a prosumer needs to make sense of the reports provided by the UI integrated into an in-home display (e.g. forecasts about own demand and generation capacity, merged with other data such as energy prices, market situation or weather conditions) to decide how much energy to buy or sell. Due to the symbiosis of the physical and virtual worlds provided by the CPS technology embedded in SM, data about energy usage is available to the customer even down to the level of separate appliances. Whereas analysis of consumption, generation, and other data can be to a great extent automated by using big data analytic tools, on prosumer tacit knowing – an internal act involving personal needs, beliefs, values, know-how, and emotions - it will depend what sense will be made out of (articulate, explicit) analytics reports and what kind of decisions will follow. As well, in an attempt to make sense of available data, prosumer will attend to the factors such as the needs of other members of the household, personal and household income. Accordingly, prosumer might decide to set automated alerts based on these specific consumption and generation patterns, specific needs, and preferences to track trading progress against these goals. In other words, the dialogic activity between a prosumer and information provided by the UI – due to inarticulable tacit components involved in it – is inherently indeterminate and irredeemably local (Tsoukas, 1996, p. 19). Due to prosumer`s emergent act of tacit knowing, which is a part of the “social context the details of which cannot be fully described *ex-ante*” (Tsoukas, 1996, p. 19), reports received via UI become relevant in concrete situations. Recalling Polanyi`s thoughts regarding duality of knowledge, a prosumer brings inarticulable tacit background and creates meanings by relying on the internal tacit act which connects these inarticulable components to the articulate focus of attention - data and information embedded in the reports. It is through this interaction that the *ba* is activated and insights (new knowledge) emerge; if separated from *ba*, reports are merely data and information, which can then be communicated digitally, independently from *ba*.

5. Discussion

According to the presented knowledge dynamics model, the SG ecosystem is a dual-loop system: one loop consisting of the physical layer and the cloud and the other consisting of the cloud and the interface layer. The cloud (with embedded computational entities) serves as the mediator of interactions between humans and machines. Industry 4.0 re-shapes actor-to-actor interactions by allowing increasing substitution of human-based interactions with M2M and Machine-to-Cloud interactions. The bidirectional interaction among distributed and autonomous SOs and their symbiosis with the virtual layer promises to equip physical systems with adaptive emergent capabilities that commonly characterize social and biological systems, where the outcomes are more complex than the individual behaviors from which they emerge (Leitao et al, 2016). Heterogeneous SOs exhibit self-organizing and self-correcting behavior, which enables their greater resilience in dynamically changing data conditions, that is, enables them to cope with disruptive events and to coordinate various actions within the ecosystem, such as handling of temporary shortages of energy supply. Autonomous and real-time decision making is enabled with no easily visible external interventions in a largely self-organized manner.

Nevertheless, what the operationalization of the model above aimed to demonstrate is that in value co-creation SOs handle automated activities (big data processing and analytics) but the broader context, comprising human factors and their tacit knowledge stays out of the SOs reach. SOs can pick up and learn about only the isolated features of the environment. As discussed in this paper, we consider human involvement and interaction as necessary for insights to be evoked from big data analytics reports and subsequent decisions, for example, regarding consumption. Moreover, individual customer needs can be met - which is one of the main value promises of Industry 4.0 (e.g. Kagermann et al. 2013) – not only because of smart use of analytics but as well because the architecture enables more opportunities for human tacit engagement which reflects their unique and variable needs.

Table 2. Comparison between the old and Industry 4.0 value creating ecosystems (adapted from Lee et al., 2016)

	Old industrial approach	**Industry 4.0 vision**
Value Objective	To integrate operations with the functional objectives of an enterprise through the use of tether-free web communication and predictive analytics with an aim of product creation and delivery	To intertwine industrial big data, smart analytics, and human tacit contribution to unveil the non-obvious, hidden relationships and patterns in big data and support evidence-based decision making, resilient performance, and collaborative product-service creation

Enabling technology	Networked and remote monitoring	Cyber-physical systems, IoT&S, cloud computing
Main characteristics	Limited self-configuration, automation pyramid hierarchy, one-directional collaboration within a system	Highly reconfigurable, decentralized, cyber-physical system automation, bi-directional collaboration within a system, highly integrated
Physical layer		
Value source	Sensors & controllers & networks	Sensors embedded in SOs (source of industrial big data), other sources such as business and government sources, social media (source of human-generated, and human-related big data)
Learning capability of machine actors	Control-oriented machine learning, expert-depended	Distributed big data analytics, deep learning (exploiting multilayered neural networks for self-thought learning from big data)
Virtual layer		
Network environment	Web-based and tether-free	Industrial internet, cloud-based IoT&S, service-oriented architecture
Mental/interface layer		
Human interaction	Lack of a closely coupled H2M interaction; web-based UI; limited opportunity for situational awareness and decision making action space	"Data socialization"; UI embedded in mobile, third-party cloud-based applications, and in-home displays; increased opportunity for customer`s engagement in consumption decisions; service providers can understand their customers better, and profile them for targeted services and better loyalty.
Service orientation	Limited, system infrastructure does not support customers in choosing the way they consume energy	Opening data to customers - the opportunity for innovative value-added service development

Overall, understanding of knowledge dynamics underlying value co-creation in Industry 4.0 helps to shed light on the revolutionary shifts occurring in industrial systems. Table 2 provides an overview of the characteristics of the vision of new cyber-physical based industrial systems that evolved from industrial approaches such as traditional grids and e-manufacturing (adapted from Lee et al. 2016).

Lastly, it is important to emphasize that a vision of a highly dynamic, self-configuring, thoroughly distributed, networked, and resilient Industry 4.0 built from CPS – despite the successful implementation examples - is still at early stages of implementation in most current industries (Wilkesmann and Wilkesmann, 2018). Further transformation requires tackling several fundamental machine and human-related challenges to bring it one step closer to this vision, which we summarize as follows:

- A fundamental part of the upcoming challenges is to address heterogeneous data sets coming from multiple sources (e.g. different types of sensors). This requires standardization of big data formats, semantic descriptions of their content (meta-data), models and architectures for achieving: a) SOs` virtualization by creating their representation in the virtual layer; b) seamless interoperability and connectivity among different applications; c) integration and aggregation of the SOs resources into value-added services for end users (Lee et al., 2016; Miorandi et al, 2012). One of the major challenges is as well achieving cyber-security in cloud environments (Lee et al., 2016). Noteworthy is recent research work conducted by Munshi and Mohamed (2017, 2018) which tackles some of these challenges in the SG domain.
- Thought provocative challenge, emanating from emergent and self- properties of new industrial systems (and, relatedly, developments in robotics and artificial intelligence) was put forward by Leitao et al. (2016, p. 8): "Since the emergent behavior is difficult to predict, a pertinent challenge is related to the development of mechanisms that ensure that not expected and not desired properties will not emerge in this complex and non-linear process". There is as well a necessity to further inquire into the differences between the emergent properties of the human and technical systems.

6. Implications for academic research and practice

We develop and present the model which serves as a theoretical base to investigate and advance the understanding of the knowledge dynamics underlying the value co-creation in new Industry 4.0 ecosystems. We suggest that the three-layer conceptualization of knowledge dynamics is instructive when attempting to address these issues. Knowledge-based activities undertaken by various actors intersect and mutually contribute to value co-creation. By exemplifying in theoretical terms constructs underlying such knowledge dynamics, we contribute to creating theory-based knowledge on the knowledge dynamics in Industry 4.0.

The model developed in this paper has important implications for knowledge strategy planning which aims to link the way how knowledge is perceived in the organization with the corporate strategy and KM programs (e.g. Bolisani and Bratianu, 2017). The more holistic approach is required which would link the knowledge-based interactions to their enabling conditions (cf. Wei Choo and Correa Drummond de Alvarenga Neto, 2010). We thus argue for the necessity of industrial firms to strike a balance between better targeting their investments in methodologies supporting the two types of knowledge-based activities, as well as training and recruitment policies — those focusing on big data-driven analytical skills, and the ones involving intuitive and analytical, emergent human knowing required for handling contextually specific, ambiguous, ill-defined tasks that the human mind is uniquely capable of tackling. An interesting avenue for industrial practitioners interested in strengthening and enabling tacit knowing (in contrast to transferring or storing it), as already emphasized in literature, would be to invest in methodologies that utilize simulated experiences that focus on perceptual skills, intuition, and pattern recognition, such as game simulations and scenarios (c.f. Klein, 2015).

7. Limitations and future research

One limitation of the knowledge dynamics model presented in this paper is that it is an initial conceptual study and as such provides only a basis for further research work. Humans-in-the-loop further require taking into consideration the questions of what is the application domain, tasks performed, and the type of data used (Leitao et al., 2016), for which indirect knowledge elicitation techniques can be used (cf. Yip and Lee, 2017). Coming back to three accounts of *ba*, to model tacit engagement of the human actors and to utilize the potential of this engagement, one would further need to consider: a) which actors are participating in various interaction combinations and where are they occurring (*ba* as a location); b) what are different (tacit) personal, social, and cultural components that are relevant to the situation at hand (*ba* as an existential space); c) what are enabling conditions which would support human tacit contribution in these interaction combinations (*ba* as an enabling context). Further research would particularly need to focus on the specificities of the enabling contexts for H2M interaction. In this sense, a key question relates to the possibility of improving the engagement of human actors with the information received via UI.

8. Conclusion

New technological advancements are giving rise to the fourth industrial revolution. The fact that Industry 4.0 is unfolding with us humans as its active shapers, gives us a unique opportunity to ensure it is “empowering and human-centered, rather than divisive and dehumanizing” (Schwab, 2017, p. 4). In this study, concerning this matter, we have proposed a theory-informed model of knowledge dynamics with a particular goal to open the black box of the role of humans-in-the-loop in the digitalized Industry 4.0 environment. This study represents an initial attempt of understanding knowledge dynamics phenomenon from a holistic perspective, by integrating knowledge-based activities of SOs, computational entities embedded in the cloud, and humans. In the end, and in a reference to huge promise of the application of artificial intelligence in Industry 4.0, we would like to emphasize that the conceptualization based on the constructivist view on knowledge advocated in this paper necessarily leads towards what we perceive to be an extremely important project of “harnessing computation to enhance human intelligence” (Anderson, 2003, p. 126), rather than replacing it.

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