Received: 22 January 2020 | Revised: 19 May 2020 | Accepted: 19 May 2020

DOI: 10.1002/eng2.12217

PERSPECTIVE

WILEY

What is knowledge in Industry 4.0?

AMM Sharif Ullah

Division of Mechanical and Electrical Engineering, Kitami Institute of Technology, Kitami, Japan

Correspondence
AMM Sharif Ullah, Division of Mechanical and Electrical Engineering, Kitami Institute of Technology, 165 Koen-cho, Kitami 090-8507, Japan.
Email: ullah@mail.kitami-it.ac.jp

Abstract

Industry 4.0 relevant systems (eg, cyber-physical systems, digital twins, and alike) need digitized knowledge to function. Before digitizing knowledge, a fundamental question arises: What is knowledge? In order to answer this question, this study first reviews the definitions of knowledge found in the extant literature of epistemology, engineering design, manufacturing, organization science, information science, and education science. Since the definitions reported so far are not succinct and suffer circularity, this study overcomes this by introducing a three-element-based definition of knowledge—a piece knowledge consists of three elements defined as claim, provenance, and inference. This results in four types of knowledge defined as definitional, deductive, inductive, and creative knowledge, and each type of knowledge is again divided into some categories. Some real-life scenarios relevant to engineering design and manufacturing are used to clarify the proposed knowledge types/categories; the relevant pieces of knowledge are represented by knowledge graphs (concept maps) for the sake of digitization. The myriad proximal and distal relationships between knowledge and other relevant entities (human/machine learning, logical inferences, experimental data, analytical results, creative thinking, and cognitive reflections) become succinct and transparent due to the proposed definition of knowledge. Consequently, this study establishes the fundamentals of developing sophisticated methods and tools for the advancement of Industry 4.0.

KEYWORDS

creativity, cyberphysical system, engineering design, Industry 4.0, knowledge-based system, manufacturing

1 | INTRODUCTION

"Knowledge is Power"—Francis Bacon.

Engineering problems cannot be solved without applying knowledge. Consequently, knowledge-intensive activities, such as knowledge acquisition, representation, dissemination, utilization, and management, play a vital role in engineering problem-solving. The advent of systems engineering[1] and engineering informatics[2] has added a new dimension—digitization of knowledge-intensive activities with the aid of advanced computing, information, and communication technologies. The remarkable thing is that such advanced computing, information, and communication technologies have coined a concept of manufacturing systems called the fourth industrial revolution (popularly known as Industry 4.0 or smart manufacturing).[3-9] In Industry 4.0, humans, technology, and organizations are integrated in both horizontal and vertical manners using advanced information and communication technologies.[3,4] The integration must result in some intelligent enables that help achieve the manufacturing tasks through data integration from agile sources.[5] At the same time, the data must be transformed into knowledge,[9] enabling seamless integration between physical and cyber spaces.[7,8] This results in some embedded systems (eg, cyberphysical systems) that can perform high-level cognitive tasks such as monitoring, understanding, predicting, deciding, acting, and adapting.[7,8,10] Without applying digitized knowledge, these systems cannot perform the abovementioned cognitive tasks. As a result, digitization of knowledge-intensive activities (knowledge acquisition, representation, dissemination, utilization, and management) is critical for the advancement of Industry 4.0.

However, the embedded systems underlying Industry 4.0 perform the above-mentioned cognitive tasks to support engineering design and manufacturing processes autonomously. Numerous authors have studied the engineering design and manufacturing knowledge representation and reuse.[11] It is emphasized that the underlying knowledge management framework must incorporate some mechanisms that semantically classify engineering design and manufacturing knowledge.[12] Pomp et al[13] and Paulus et al[14] developed a system (ESKAPE) where the semantically annotated data structures (or knowledge graph) are utilized to deal with the computational complexity of knowledge representation and knowledge sharing within the constituents of Industry 4.0. Nevertheless, when a digitized engineering design and manufacturing knowledge management systems are constructed, the systems become domain specific and web technology specific. For example, Chhim et al[15] developed a knowledge representation system for design failure mode and effects analysis (DFMEA) and process failure mode and effects analysis (PFMEA) using some high-level concept maps (user-defined ontology) from the context of the semantic web. The main problem of these systems is their scalability and user-friendliness because the underlying knowledge representation depends heavily on the query language and data access protocol (SPARQL) customized for the resource description framework (RDF). Thus, these systems are, by nature, esoteric. On the other hand, as far as the customer needs elicitation and small/medium enterprises are concerned, knowledge sharing is a bottleneck of Industry 4.0,[16] which needs further research.

In general, knowledge makes a vast ecosystem integrating human learning, machine learning, logical inferences (deduction, induction, and abduction), experimental data, analytical results, simulations, algorithms, creative thinking, and cognitive reflections. In most case, data and knowledge are used interchangeably (eg, compare the articles[5,8,9,13-16]). The myriad proximal and distal interactions of knowledge among the abovementioned entities result in heavy computation. The computational complexity cannot be tackled if the concept of knowledge is succinctly defined.

The above descriptions indicate that before developing methods and tools needed for achieving the desired level of digitization of knowledge-intensive activities from the context of Industry 4.0, the following questions must be addressed. What is knowledge? What are the types of knowledge? How to create knowledge? How to represent knowledge in a domain-independent manner? What is the difference between data/information and knowledge? What is the role of human cognition in knowledge formation? What is the role of experience in knowledge formation? Is the attainment of "true" knowledge possible? Is analytical knowledge better than experiential knowledge? How to digitize the represented knowledge without web-specific query programming? The abovementioned questions are challenging to answer since a relatively unambiguous, succinct, and circularity-free definition of knowledge is not yet available. This can be understood from a relatively compressive account on the definition of knowledge presented in Section 2. For the sake of introduction, three commonly used definitions of knowledge are considered as follows.

Consider the following three general views regarding knowledge. (a) First, consider the most general view regarding knowledge—a piece of knowledge is a proposition that corresponds to justified true belief.[17] The process of justifying the truthfulness of a belief involves several intellectual resources, and the process capable of making justification of a belief possible may not be known beforehand. Thus, "true knowledge" may not exist. (b) Second, consider the dictionary meaning of knowledge. For example, a dictionary-based definition describes knowledge as an awareness, understanding, or information, which either resides within a person's mind or is possessed by people and can only be obtained via experience or investigation.[18] This is a rather broad definition of knowledge involving other concepts requiring prior definition. (c) Finally, consider the definitions of knowledge given by legislative bodies. For example, the European Union defines knowledge as facts, principles, theories, and practices accumulated by learning; both cognitive reflections and direct experiences of individuals or groups contribute to the body of knowledge.[19]

The remarkable thing is that the definitions of knowledge (the above ones and the ones presented in Section 2) are based on several concepts. For example, the last definition mentioned above associates concepts such as learning, cognitive reflection, direct experience, fact, principle, theory, and practice, to define the knowledge. Such concepts must be defined before defining knowledge. This results in a phenomenon called circularity that must be avoided while defining knowledge.[20] Therefore, defining knowledge in clear terms, at the same time avoiding circularly, is a challenging task. This article aims to present a circularity-free and unambiguous definition of knowledge that can help build knowledge-based systems from the context of Industry 4.0.

The remainder of this article is organized as follows. Section 2 presents a comprehensive review of definitions of knowledge reported in extant literature concerning epistemology, engineering design, manufacturing, as well as organization science, education science, and information science. Section 3 presents a revised definition of knowledge along with its different types and categories. Section 4 describes the types and categories of knowledge presented in Section 3 using some real-life examples. The representation of knowledge using knowledge graphs (concept maps) is also presented in Section 4. Section 5 discusses the implications of this study by demonstrating the existence of different types and categories of knowledge in a creative design process. This section also suggests a framework for developing knowledge-based systems for the advancement of Industry 4.0. Section 6 presents the concluding remarks drawn from this study.

2 | LITERATURE REVIEW

Three commonly known definitions of knowledge are very briefly presented in the previous section. However, the concept of knowledge and its definitions have been studied at great depth in epistemology. This section thus, first, reviews the definitions of knowledge found in epistemology. The definition of knowledge has also been studied in other relevant disciplines. Subsequently, this section reviews the definitions of knowledge found in the literature of engineering design, manufacturing, and organization, information, and education sciences.

2.1 | Epistemology

Epistemology is the philosophical study that deals with the nature, origin, and formulation of knowledge irrespective of the academic discipline.[21,22] The definition of knowledge in epistemology exhibits multiplicity, which has lasted since the period of Aristotle. Multiplicity originates from such metaphysical concepts as idealism, rationalism, empiricism, neutralism, pragmatism or evolutionism, and explanationism. Each metaphysical concept corresponds to certain truths that manifest knowledge. In particular, idealism considers there exist unquestionable and transcendental truths that are entirely independent of experiences. Rationalism considers that there exist rational processes that are somewhat independent of experiences, thereby leading to some truths. Empiricism considers all truths to be dependent on experiences, that is, the experience is the sole driver that contributes to knowledge formation. Pragmatism adopts a skeptic or evolutionary view toward truth, that is, the usefulness of the perceived truth determines its fate—whether or not it will be considered a piece of knowledge. Consequently, truthfulness may vary with time. Neutralism is similar to pragmatism and considers that while finding truth, any metaphysical concept from among idealism, rationalism, and empiricism can be used. This implies that truth is not biased to a specific metaphysical concept, and that any combination of metaphysics can be used to formulate knowledge. Explanationism considers that a so-called scientific truth evolves following the deductive-nomological (D-N) explanation, inductive-statistical (I-S) explanation, or statistical-relevance (S-R) explanation.[23-28]

In classical epistemology, definitions of knowledge proposed by Hume and Kant have attracted significant attention. According to Hume, knowledge corresponds to two propositions: relations of ideas and factual matters (referred to as matters of fact).[29] Relations of ideas are a priori nonfalsifiable propositions (eg, a triangle has three sides, the summation of all included angles of a triangle equals 180°, and alike). Matters of fact are experience-dependent propositions that can be falsified if a counterexample is available (eg, apples are good for health, bachelors are messy, and alike). Kant, on the other hand, analyzed the work of Hume and proposed there exist three types of knowledge—analytic a priori, synthetic a priori, and synthetic a posteriori[30] Analytic a priori knowledge is always true because these are mere definitions of ideas (eg, a triangle has three sides, all unmarried males are bachelors, and alike). Synthetic a priori knowledge is deduced from a set of analytic a priori knowledge (eg, $4 + 7 = 11$, the summation of all included angles of a triangle equals 180°, and alike). Thus, the knowledge gained from mathematical and geometric derivations falls under the category of synthetic a priori knowledge. Synthetic a posteriori knowledge corresponds to knowledge gained through experience (eg, apple is good for health, bachelors are rich, and alike). In addition, Kant considered the existence of four concepts or categories of pure understanding—quantity, quality, relation, and modality—which correspond to humans' ability to organize their experiences and formulate synthetic a posteriori knowledge. These four categories, in turn, entail 12 concepts of judgment. Specifically, quantity entails the concepts of unity, plurality, and totality; quality entails reality, negation, and limitation; relation entails inherence and subsistence, cause and effect, and community; and finally, modality entails possibility-impossibility, existence-nonexistence, and necessity and contingency. Although Hume and Kant are considered empiricists and rationalists, their definitions of knowledge possess certain similarities. For example, Hume's relations of ideas correspond to experience-independent knowledge, which Kant classified into two categories—analytic a priori and synthetic a priori. Both Hume and Kant categorized experience-dependent knowledge into a separate category. Hume classified it as matters of fact, whereas Kant considered it as synthetic a posteriori.

Apart from the Hume- and Kant-based definitions of knowledge, there exist other definitions of knowledge in epistemology. According to Russell.[31,32] there exist two types of knowledge—by acquaintance and by description. Knowledge by acquaintance implies knowledge gained by direct awareness or experience of a knower and is free from any intermediary inference processes. Knowledge by description, in contrast, is a propositional truth acquired via inferential, mediated, or indirect processes. Such definitions of knowledge explicitly specify the role of the knower in knowledge formulation. Many authors have investigated knowledge from the perspectives of acquaintance and description and provided epistemological descriptions of acquaintance and descriptive knowledge.[33,34] Meanwhile, new metaphysics have also been added while formulating knowledge by prioritizing the knower. For example, Zagzebski[20] considered that knowledge formulates when knowers try to build a relationship with a portion of reality through consciousness. Knowers might directly or indirectly be related to a portion of reality. Therefore, knowledge depends on knowers' cognitive abilities and emotional attachment with a portion of reality, that is, the knower's role must be quantified while defining knowledge. Accordingly, Zagzebski[20] defined knowledge as a cognitive contact with reality arising out of acts of intellectual virtue. This implies that "intellectual virtue" is a metaphysical quantifier of the knower with regard to knowledge formulation. However, intellectual virtue can be defined in two different ways[35] that depend on the concept of reliability[21,36] and responsibility.[20,35] The above definition of knowledge is based on responsibility (open-mindedness, courage, critical thinking, moral obligation, and alike).

2.2 | Engineering design and manufacturing

Like its predecessors, in Industry 4.0, it is highly likely that seamless execution of engineering design and manufacturing (ie, product, system, and service conceptualization and realization) gets the highest priority. Thus, how the concept of knowledge has been treated in engineering design and manufacturing must be elucidated before proposing a clear and circularity-free definition of knowledge.

First, consider engineering design (product, system, and service conceptualization). Engineering design is a purely knowledge-intensive activity.[37] Therefore, certain design theories explicitly highlight the contribution of knowledge in the execution of a design process. For example, let us consider the general design theory[38-41] and C-K theory of design.[42-45] Following the general design theory.[38,39] the execution of a design process requires knowledge manipulation, wherein "knowledge" may either be of the ideal or real types.[40,41] This ideal/real knowledge plays its role through logical processes of deduction and abduction[41] as described in Section 3. Both knowledge types assist in making necessary decisions concerning the continuation of a design process under given circumstances.[41] Nevertheless, ideal or real knowledge types can be defined with respect to other concepts, such as the "entity" and "topology" of the design space.[40] which must be defined before defining the knowledge types. This injects circularity in the definition of ideal or real knowledge, in addition to certain logical ambiguities caused by induction (Section 3). In addition to deduction and abduction (refer to Section 3 for definitions), another logical process called induction[46] must be considered when processing real knowledge. This is because induction extracts knowledge from experiences and experimental data. In addition, the role of induction is not explicitly highlighted when processing real knowledge within the framework of the general design theory, thereby imparting ambiguity in the general-design-theory-based definition of knowledge. By contrast, the C-K theory of design considers the simultaneous evolution of two domains—concept and knowledge—when a design process continues.[42,43] Application of this theory requires two knowledge types—existing and new—for continuing a design process.[42-45] New knowledge is necessary to resolve epistemic uncertainties underlying creative concepts.[43] Unlike the general design theory, the C-K theory does not define new-knowledge creation or existing-knowledge utilization processes in terms of deduction, abduction, induction, and alike. Consequently, C-K-theory-based definitions of knowledge are somewhat informal.

Similar to engineering design, in manufacturing (product, system, service realization), the concept of knowledge has always existed. It appears more explicitly owing to the advent of Industry 4.0. Industry 4.0 employs embedded systems (eg, cyberphysical systems) to perform cognitive tasks such as monitoring, understanding, predicting, deciding, acting, and adapting. Some authors reckon that the cyberphysical systems are nothing but an extensive and self-growing knowledge base,[8] but knowledge is not defined clearly. On the other hand, some authors consider that the contents by which the embedded systems perform, take the form of digital twins—exact mirror images of real-world objects, processes, and phenomena—in cyberspace.[7,47] Some of these twins consist of different types of knowledge.[7] but these types are not clearly defined. Some other authors (eg, consider the work in[48]) reckon that both data-bases and knowledge-bases must populate the embedded systems, where the demarcation lines between "data" and "knowledge" are not drawn. Some authors consider that knowledge is semantically annotated data,[13-15] as already described in Section 1. Thus, in the literature of Industry 4.0, the concept of knowledge remains ambiguous.

2.3 | Other relevant fields

In addition to epistemology, engineering design, and manufacturing, definitions of knowledge have also been reported in the literature of other fields such as organization, education, and information sciences.

A well-known definition of knowledge in organization science states that knowledge can either be of the tacit or explicit types.[49-53] Tacit knowledge pertains to intuitions, experiences, and know-how possessed by active individuals in their respective organizations. Consequently, it is challenging to identify or even codify such knowledge.[49,50,53] Explicit knowledge includes documented instructions for facilitating organizational activities. It is, therefore, easy to identify and share. Tacit knowledge dynamically transforms into explicit knowledge and vice versa through social or teamwork-based interactions (dialogue) among employees.[52] Remarkably, such transformations do not require formal logical processes.[50,51] This contradicts the definitions of knowledge reported in other disciplines, such as information science. However, other schools of thought in organization science exist related to knowledge[54] and its formation.[55] For example, Albino et al[54] considered five types of knowledge—scientific, quantitative, qualitative, tacit, and intuitive. As reported by Boh.[55] knowledge formation and validation processes follow a hierarchy that is not clearly defined.

In education science, the concept of knowledge has always existed along with human-learning. For example, consider the definitions of knowledge presented in[56-58]. Carson[56] has proposed nine categories of knowledge—empirical, rational, conventional, conceptual, cognitive-process skills, psychomotor, affective, narrative, and received. All these categories of knowledge form in the intertwined domains, and ultimately transform to conventional knowledge. Kinchin et al[57] have proposed four types of knowledge, namely, novice knowledge, theoretical knowledge, practical knowledge, and professional knowledge. All these types of knowledge possess different degrees of "semantic gravity." Ullah[58] has proposed five types of knowledge—analytic a priori, synthetic a priori, synthetic a posteriori, meaningful, and skeptic—for discipline-based education. The first three types follow the Kantian epistemology described in Section 2.1 and form in the cognitive and real worlds, whereas the last two types of knowledge form in the pragmatic world, where the preferences of the knowledge formulator and the purposes of application become the main ingredients of knowledge. Nonetheless, the definitions of knowledge in[56-58] are somewhat informal and defined linguistically, only.

In information science, the concept of knowledge has always existed along with the concepts of information and data wherein data, information, and knowledge have been used interchangeably. These concepts have started to play an explicit role in engineering problem solving when several machine-learning approaches have been introduced[59-65] to facilitate learning from a given data set. This enables expert systems to solve domain-specific problems.[60] At the core of these systems lie certain rules (eg, if … then … rules) extracted from a given data set using probabilistic reasoning and fuzzy logic.[66,67] Therefore, in information science, machine-learning-enabled rules have been playing the role of knowledge. A few authors in information science have formally defined knowledge with regard to data and information.[62,68] Nevertheless, these definitions suffer circularity. For example, consider the definitions reported in[62,68] Nagao[62] has classified knowledge into two types—factual and inference-based. Factual knowledge is obtained objectivity, accepted widely, and can be expressed as a sentence or symbolic equation, wherein each term is clearly defined. In order to represent factual knowledge, other concepts (referred to as primary and secondary information)[62] can be used as semantic annotations for ease of digital-media-based information processing. On the other hand, using inferences (deductive, inductive, or probabilistic),[43] cognitive reasoning (analogical, common sense, and qualitative), and heuristics, new knowledge can be acquired from factual knowledge. Such knowledge is called inference knowledge.[62(p9-16)] Mizzaro[68] has introduced a concept called knowledge-state to draw demarcation lines among knowledge, information, and data. Although the temporal nature of a knowledge-state has been studied,[68] the types of knowledge have not been shown explicitly in terms of knowledge state or data/information.

3 | REVISED DEFINITION OF KNOWLEDGE

The previous section describes the multiplicity and circularity underlying the definitions of knowledge as elaborately as possible, referring to different fields (epistemology, engineering design, manufacturing, organization science, education science, and information science). This section presents a revised definition of knowledge from the perspective of Industry 4.0. Before presenting the revised definition, the following points are highlighted for the sake of better understanding.

Despite the multiplicity and circularity in the definitions of knowledge described in the previous section, there are some common grounds. One of the noteworthy common grounds is related to the representation of knowledge-knowledge graphs (eg, concept maps) can represent knowledge irrespective of its types, human-learning, machine-learning, and academic fields. To understand this, recall information and education sciences, as described above. In information science, where machine-learning is the primary concern, knowledge representation boils down to concept mapping. For example, the types of knowledge called factual and inference knowledge[62] are represented using semantic networks of concepts wherein the logical operations (AND, OR, NOT, and alike) connect the relevant concepts manifesting a set of if … then … rules.[62] In education science, where human-learning is the primary concern, knowledge representation also boils down to concept mapping. For example, Kinchin et al[57] and Ullah[58] represented various types of knowledge using concept maps. A concept map here is a personalized ontology of human understanding regarding a given issue.[67-72] These types of maps ultimately refer to the assimilation hypothesis of human learning.[73] The remarkable thing is that the technology of semantic web wherein the machine and human-readable knowledge and linked data will reside for using them in Industry 4.0 will rely on the knowledge graph-based data-format (ie, concept mapping).[74,75]

On the other hand, there are some disputed grounds. For example, consider the role of logical operations in knowledge formation. There is a split in this regard. To understand this, recall the recall information and organization sciences, as described above. Information science demands the application of logical operations for knowledge formulation and transformation, for example, factual-inference knowledge transformations require sophisticated logical operations.[62] Organization science demands the application of social interactions—tacit-explicit knowledge transformations only require social interactions.[50]

Drawing the demarcation lines among knowledge, data, and information has been an important issue. Though knowledge-state[68] may be used to solve this problem, it would be challenging to implement it in real-life scenarios without the types of knowledge. Though the semantic networks of linked data and knowledge (ie, knowledge graphs or concept maps) integrate the relevant data, information, and knowledge to solve problems in engineered systems,[76-78] the maps are created without making any distinctions among knowledge, data, and information. As a result, when the so-called knowledge state[68] changes, its influence randomly propagates to the whole network. This means that what has been affected (knowledge, data, or information) to what extend remains obscure. On the other hand, human-learning described so far is based on the assimilation hypothesis.[73] which states that nothing new can be learned without existing knowledge. This contradicts the concept of new knowledge given by the C-K theory of design,[43] and is not desirable because new knowledge is the primary ingredient for creating artifacts. Thus, education-science-driven definitions of knowledge tend to ignore the main ingredient of creativity. On the other hand, which segment of a knowledge graph or concept map is knowledge and which part is not must be known beforehand. This is not possible until a clear demarcation line exists between knowledge and other relevant contents (eg, data and information). At the same time, the relevant system must aware of the coexistence of different types of knowledge. This is a drawback of the existing knowledge and data representation using the semantic web.[74,75]

Based on the abovementioned considerations, this section presents an Industry 4.0- and semantic web-friendly definition of knowledge, which is free from circularity and ambiguity.

The proposed definition of knowledge is as follows. A piece of knowledge (denoted as K) comprises three elements—knowledge claim (K_{clm}), knowledge provenance (K_{prv}), and knowledge inference (K_{inf}). In general, these elements demonstrate the following relationship.

$$K = \{K_{\text{clm}}, K_{\text{prv}}, K_{\text{inf}}\} \quad K_{\text{prv}} \overset{K_{\text{inf}}}{\rightarrow} K_{\text{clm}} \tag{1}$$

In the above expression, K_{clm} denotes a manifestation of K, that is, K_{clm} can be a proposition, an equation, or any other piece of information. Other elements may or may not be reported explicitly, that is, K_{prv} and K_{inf} may remain empty, but $K_{\text{clm}} \neq \emptyset$. K_{prv} helps identify the truthiness of K_{clm}. There exist no restrictions that K_{clm} must be "completely true" or "completely false." Partially true or partially false K_{clm} can be used to manifest K. This implies that K_{prv} may not fully justify K_{clm}. K_{inf} refers to the inferential process involved in gaining K_{clm} in the presence of K_{prv}. In addition, K_{inf} helps categorize K into different types and categories. In some cases, K_{prv} and K_{inf} may remain empty that is, $K_{\text{prv}}, K_{\text{inf}} = \emptyset$ is allowed.

The definition of knowledge given by Equation (1) yields four fundamental knowledge types—(a) definitional, (b) deductive, (c) inductive, and (d) creative—which are summarized in Table 1 along with their main characteristics and descriptions.

As described in Table 1, definitional knowledge refers to knowledge gained by defining ideas or concepts such that their definitions are not uncontroversial or readily accepted by stakeholders. For definitional knowledge, $K_{\text{clm}} = K_{\text{prv}}$ and $K_{\text{inf}} = \emptyset$. Since such pieces of knowledge correspond to mere definitions of ideas, they are always true (tautology). From an epistemological sense, such knowledge qualifies as analytic a priori knowledge, as described in Section 2. This type of knowledge can be further explained using examples discussed in Section 4.

Deductive knowledge implies knowledge gained by establishing relationships among definitional knowledge with the aid of a logical process called deduction. Mathematically,

$$\text{Deduction} : (A \rightarrow B) \wedge (A) \vdash B, \quad ((A \rightarrow B) \wedge (B \rightarrow C)) \vdash (A \rightarrow C). \tag{2}$$

In the above equation, A, B, and C are, by definition, true entities, that is, they qualify as definitional knowledge.

Thus, from the viewpoint of deductive knowledge, $K_{\text{clm}} \neq K_{\text{prv}}$, $K_{\text{inf}} =$ Deduction, and K_{prv} represent pieces of definitional knowledge. From an epistemological sense, deductive knowledge refers to synthetic a priori knowledge or relations of ideas, as described in Section 2. There exist two categories of deductive knowledge—(a) primary relation of ideas and (b) secondary relation of ideas—as exemplified in Section 4.

Inductive knowledge refers to knowledge gained by experiencing the world with the aid of a logical process called induction. Mathematically,

$$\text{Induction} : (O_1, \dots, O_n) \vdash (A \rightarrow B). \tag{3}$$

In the above expression, $O_1, \dots, O_n$ refer to finite observations, experimental results, experiences, or data. Entities A and B are consistent with objects related to $O_1, \dots, O_n$. Thus, from the viewpoint of inductive knowledge, $K_{\text{clm}} \neq K_{\text{prv}}$, $K_{\text{inf}} =$ Induction, and K_{prv} correspond to pieces of data and/or observations, that is, $O_1, \dots, O_n$, as described above. Based on the nature of induction, inductive knowledge can be classified into three main categories—(a) informal-induction-based knowledge, (b) relation-of-ideas-assisted inductive knowledge, and (c) complex-induction-based knowledge. These categories have also been exemplified in Section 4.

Formulation of creative knowledge is caused by creative activities or pragmatic preferences. In this case, there exists no formal provenance that is, $K_{\text{prv}} = \emptyset$, and the logical process involved most likely corresponds to abduction, that is, $K_{\text{inf}} =$ Abduction (eg, introducing plausible *causes* ($A1, A2, \dots$) for achieving a given *effect* (B).

$$\text{Abduction} : (\text{Unknown } A \rightarrow B) \wedge (B) \vdash \text{Plausable } A1, A2, \dots . \tag{4}$$

TABLE 1 Definition of knowledge

Types of knowledge	Main characteristics	Descriptions
Definitional knowledge	$K_{\text{clm}} = K_{\text{prv}}, K_{\text{inf}} \neq \emptyset$	Knowledge due to uncontroversial definition of ideas or concepts
Deductive knowledge	$K_{\text{clm}} \neq K_{\text{prv}}$, $K_{\text{inf}} =$ Deduction, K_{prv} are some pieces of definitional knowledge	Knowledge due to deduction applied to ideas, primary relations of ideas, and/or secondary relations of ideas
Inductive knowledge	$K_{\text{clm}} \neq K_{\text{prv}}$ and $K_{\text{inf}} =$ Induction, K_{prv} consists of some pieces of data and/or observations	Knowledge due to induction applied to experience or data, resulting in informal induction-based knowledge, relations-of-ideas assisted inductive knowledge, and complex induction-based knowledge
Creative knowledge	$K_{\text{prv}} = \emptyset$ and $K_{\text{inf}} =$ Abduction (most likely)	Knowledge due to abduction (creative activities or pragmatic preferences), resulting in analytic a priori-based creative knowledge, synthetic a priori-based creative knowledge, and synthetic a posteriori-based creative knowledge

It is remarkable that the truthiness of $A1, A2, \ldots$ is neither true nor false until a new piece of deductive or inductive knowledge is available. The truthiness may refer to Kantian categories of judgment, as described in Section 2. Creative knowledge can be categorized into three types—(a) analytic a priori-based, (b) synthetic a priori-based, and (c) synthetic a posteriori-based—as exemplified in Section 4.

The proposed knowledge types and their categories, except the definitional knowledge, cannot exist independently. As a result, knowledge chains or graphs form, manifesting a concept map, or a set of concept maps. When a concept map or network is studied, its contents boil down to definitional, deductive, inductive, and/or creative knowledge. Consequently, while constructing concept maps for use in desired purposes (eg, human learning or learning in human-cyberphysical systems), their contents can be organized and analyzed in terms of the knowledge types and categories presented in this section.

4 | EXEMPLIFICATIONS

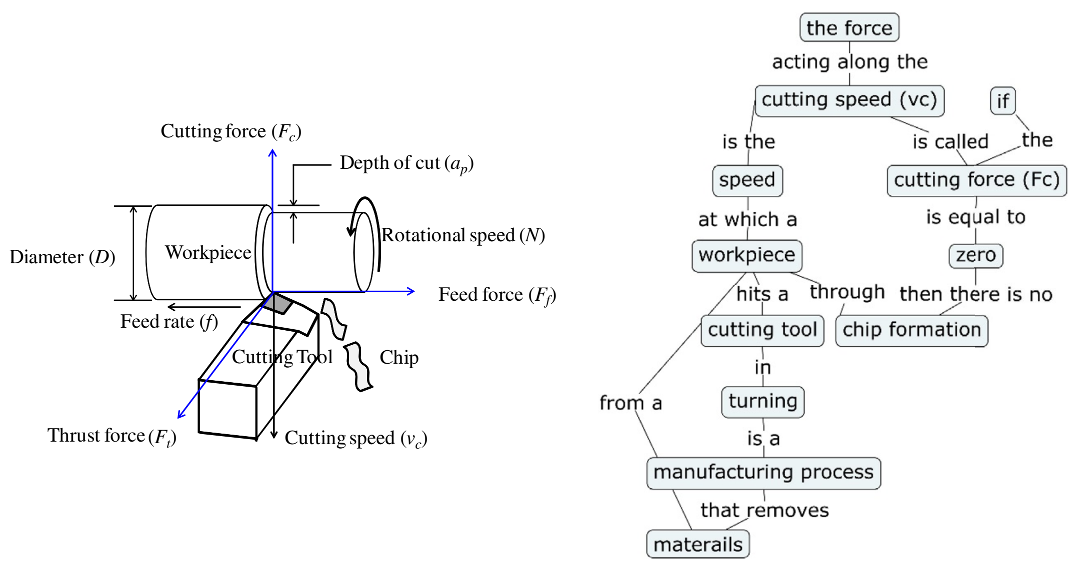
This section presents examples that describe the types and categories of knowledge presented in Section 3. Most of the examples are relevant to arbitrary scenarios underlying engineering design and manufacturing. In all examples, a knowledge graph (concept map) represents knowledge claim (K_{clm}), and in some cases, the concept maps directly point to relevant knowledge provenance (K_{prv}). In other cases, K_{prv} is either shown partially or not shown at all. Knowledge inference (K_{inf}) refers to an equation out of Equations (2)-(4), as appropriate, and it is not explicitly shown in the respective concept maps.

4.1 | Definitional knowledge

As already mentioned, definitional knowledge is created by uncontroversial definitions of ideas or concepts, and it does not rely on formal inference per se. At the same time, knowledge provenance cannot be separated from a knowledge claim. For example, consider an illustration of turning (a widely used manufacturing process) and the corresponding concept map depicted in Figure 1A,B, respectively. The concept map captures a portion of the knowledge underlying the scenario. It boils down to the following statements:

(1) Force acting along the cutting direction is called cutting force.

(2) Cutting speed refers to the speed at which the workpiece makes contact with the cutting tool while turning.



(A) A scenario of turning operation (B) A concept map underlying (a)

FIGURE 1 Examples of definitional knowledge

(3) Turning is a manufacturing process that removes materials from a workpiece via chip formation.

(4) If the cutting force equals zero, no chip formation occurs.

Since these statements define the concepts of cutting speed and cutting force during the material-removal process called turning, they can only be considered pieces of definitional knowledge. Thus, the above statements can be considered a knowledge claim and provenance simultaneously. Without these definitions, other types or categories of knowledge underlying turning (described below) do not make sense.

4.2 | Deductive knowledge

As already described, deductive knowledge comes into being due to the inference called deduction (Equation (2)), wherein knowledge claim and knowledge provenance need not be identical. Instead, the knowledge provenance here refers to the pieces of definitional knowledge. There exist two categories of deductive knowledge, namely, primary relation of ideas and secondary relation of ideas. For example, consider the concept map depicted in Figures 2 that underlies the scenario described in Figure 1A. The concept map boils down to the following statements:

(1) The manufacturing process called turning entails cutting power (P_c), material-removal rate (MRR), and specific cutting energy (K_c).

(2) Cutting power (P_c) can be expressed as $P_c = F_c v_c$.

(3) Material-removal rate (MRR) is given by $\text{MRR} = a_p f v_c$.

(4) Specific cutting energy (K_c) is given by $K_c = P_c/\text{MRR}$.

(5) $P_c = F_c v_c$, $\text{MRR} = a_p f v_c$, and $K_c = P_c/\text{MRR}$ yield $K_c = F_c/(a_p f)$.

The first statement does not qualify as a piece of deductive knowledge. It is instead a piece of informal-induction-based knowledge, as described in the next subsection. Statements (2), (3), and (4) are examples of primary relation of ideas, whereas the last statement exemplifies secondary relation of ideas, because it has been derived from statements (2), (3), and (4) using deduction.

Statement (2) entails three pieces of definitional knowledge (cutting power, cutting force, and cutting speed) that collectively refer to the knowledge provenance (when force is multiplied by speed, it yields power). This provenance, as well as the definitional knowledge about the cutting force and cutting speed, are not explicitly shown in the concept map (Figure 2). (Figure 1B, on the other hand, explicitly describes the relevant definitional knowledge.) Therefore, knowledge can be made more meaningful from a user's point of view by integrating the concept maps depicted in Figures 1B and 2, and a concept map showing the provenance mentioned above. Statement (3) entails four pieces of definitional knowledge (material-removal rate, depth of cut, feed rate, and cutting speed) that collectively refer to the provenance "material removal rate refers to the volume of material removed in unit time." Once again, this provenance and associated definitional knowledge (depth of cut, feed rate, and cutting speed) are not explicitly described in the concept map (Figure 2). Figure 1B, on the other hand, depicts a portion of the relevant definitional knowledge (cutting speed). Thus, by adding

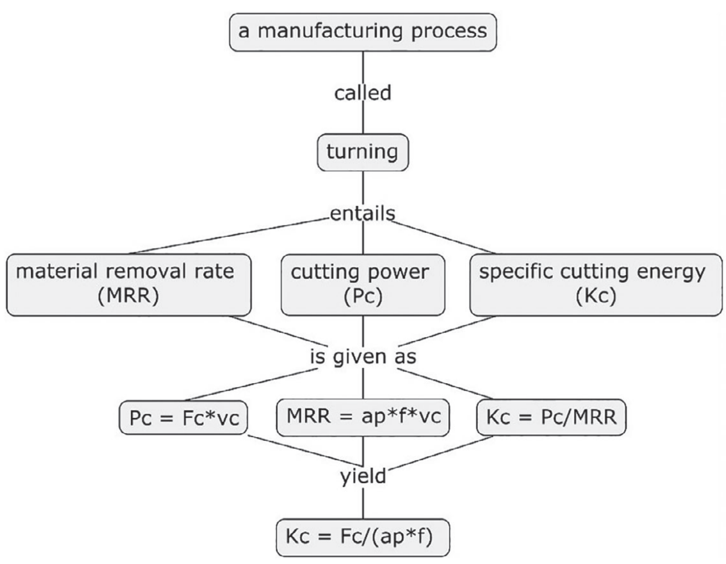


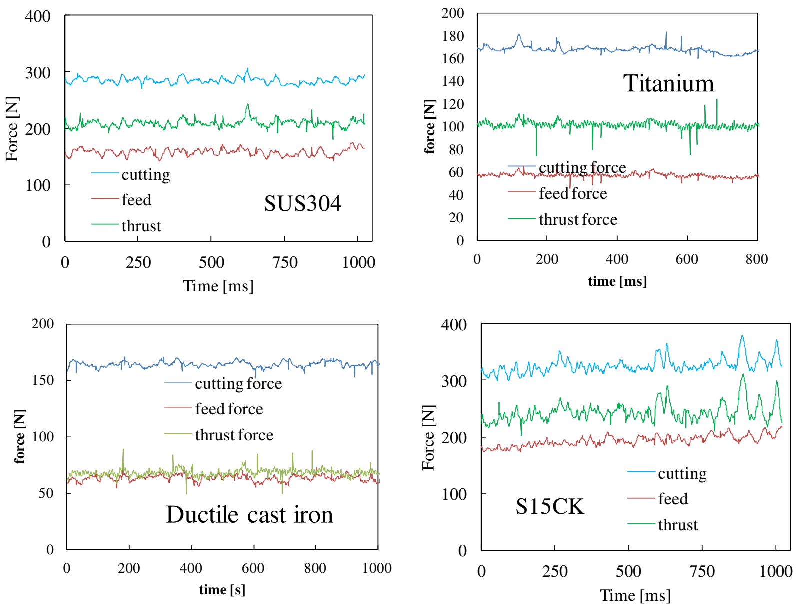
FIGURE 2 An example of deductive knowledge

definitions of the depth of cut and feed rate to the concept map depicted in Figure 1B and subsequently integrating it with the concept map depicted in Figure 2 and abovementioned provenance would make knowledge representation more meaningful. A similar argument is valid for statement (4).

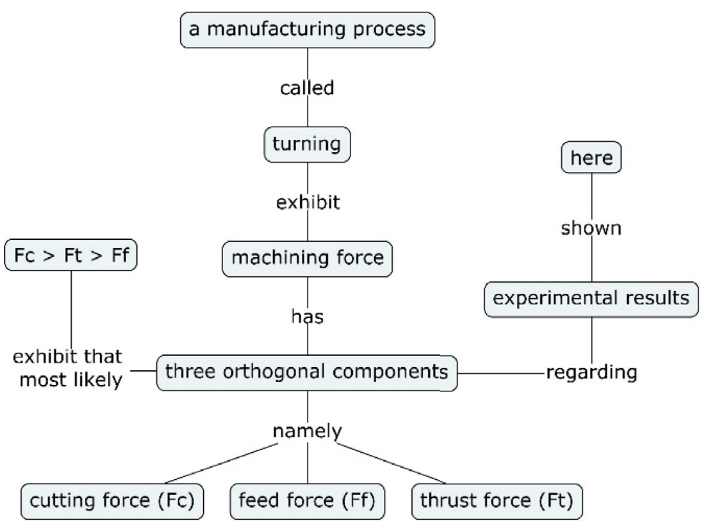
4.3 | Inductive knowledge

As already stated, inductive knowledge is caused by an inference, called induction (Equation (3)), where knowledge claim and provenance are not identical. Instead, knowledge provenance here refers to pieces of observations, experimental data, and alike. There exist three categories of inductive knowledge—informal-induction-based knowledge, relation-of-ideas-assisted inductive knowledge, and complex induction-based knowledge—described as follows.

The first category can be described using the scenario depicted in Figure 3. Figure 3A depicts plots of machining forces, such as the cutting force (F_c), thrust force (F_t), and feed force (F_f). The underlying machining experiments have



(A) some experimental results



(B) concept map

FIGURE 3 Informal induction-based knowledge been reported in[79]. Figure 3B depicts a concept map that comprises a piece of informal-induction-based knowledge that underlies the provenance depicted in Figure 3A. The concept map depicted in Figure 3B boils down to the following statements:

(1) The manufacturing process called turning exhibits machining force.

(2) Machining force comprises three orthogonal components—cutting force (F_c), thrust force (F_t), and feed force (F_f).

(3) Experimental results (shown here) demonstrate that the three orthogonal components are related as $F_c > F_t > F_f$.

The last statement is an example of informal-induction-based knowledge because it is derived by visually inspecting the data sets depicted in Figure 3A without performing any formal computations. The truthiness of such knowledge can be verified using provenance. Thus, data attached to the node "shown here" must direct users to the URL https://doi.org/10.3390/jmmp2040068 from where they can extract relevant data. The other two statements represent definitional knowledge.

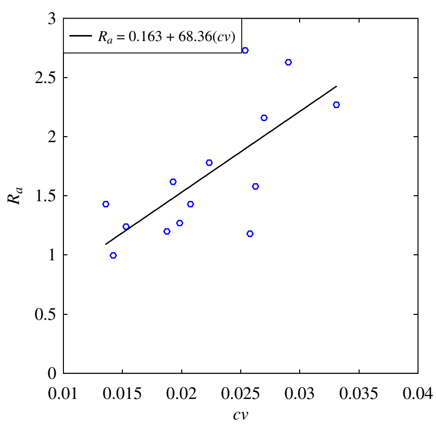
Next, consider the category of relation-of-ideas-assisted inductive knowledge. For describing this category, consider the scenario described in Figure 4. Figure 4A depicts a data set and a plot demonstrating the relationship between cutting conditions and surface roughness during turning. Thus, the provenance of inductive knowledge is presented in Figure 4. The knowledge claim is depicted in Figure 4B using a concept map.

The concept map boils down to the following statements:

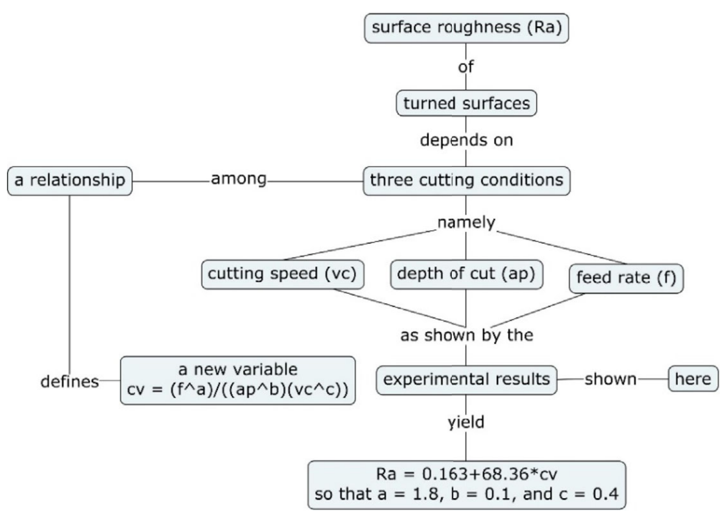
(1) Surface roughness (R_a) of turned surfaces depends on three factors—cutting velocity (v_c), depth of cut (a_p), and feed rate (f), as demonstrated by experimental results.

(2) A new variable $cv = f^a/((a_p)^b(v_c)^c)$ defines the relationship between the said three factors.

a_p [mm]	f [mm/rev]	v_c [m/min]	cv	R_a [mm]
0.84	0.3	160	0.0153	1.24
0.84	0.38	180	0.02234	1.78
0.84	0.45	200	0.02904	2.63
0.84	0.38	260	0.01928	1.62
0.84	0.45	280	0.02538	2.73
1.75	0.3	80	0.01876	1.2
1.75	0.38	100	0.02626	1.58
1.75	0.45	120	0.0331	2.27
1.75	0.3	160	0.01422	0.997
1.75	0.38	180	0.02076	1.43
1.75	0.45	200	0.02698	2.16
2.75	0.3	160	0.01359	1.43
2.75	0.38	180	0.01984	1.27
2.75	0.45	200	0.02579	1.18



(A) some experimental results



(B) concept map

FIGURE 4 Relations of ideas assisted inductive knowledge

(3) Experimental results shown here yield $R_a = 0.163 + 68.36 * cv$ so that a, b, and c equal 1.8, 0.1, 0.4, respectively.

Statement (3) is a piece of relation-of-ideas-assisted inductive knowledge because the expression for R_a is established based on a relation of ideas (cv), and it is valid only for the given data set. The other two statements do not qualify as relation-of-ideas-assisted inductive knowledge. Statement (2), in particular, is a piece of relation-of-ideas-based knowledge that defines a new variable (cv) relating existing parameters—f, a_p, and v_c—found in the provenance. Statement (1), on the other hand, is a piece of informal-induction-based knowledge evolved from the data set described in Figure 4A without the need for any formal computation. This example also demonstrates that different categories of knowledge coexist when a meaningful representation of knowledge is performed.

In a general sense, when a relatively complex machine-learning approach is adopted to understand the structure underlying a data set or observation, complex-induction-based knowledge evolves. In other words, knowledge acquired by machine learning can roughly be considered complex-induction-based knowledge. Therefore, when computational-intelligence techniques are applied to a set of data/observations, the extracted knowledge can be categorized as complex-induction-based knowledge. Examples of such techniques include probabilistic reasoning, stochastic simulation, artificial neural network, genetic algorithm, fuzzy or multivalued logic, rough sets, simulated annealing, deep learning, DNA computing, multicriteria/objective decision making/optimization, decision-tree induction (ID3, C5.0), and hidden Markov modeling.[7,47,59-67,80] For example, consider the case described in Figure 5. Figure 5A schematically illustrates two fuzzy numbers—A and B—induced from cutting-torque time-series data recorded under two sets of

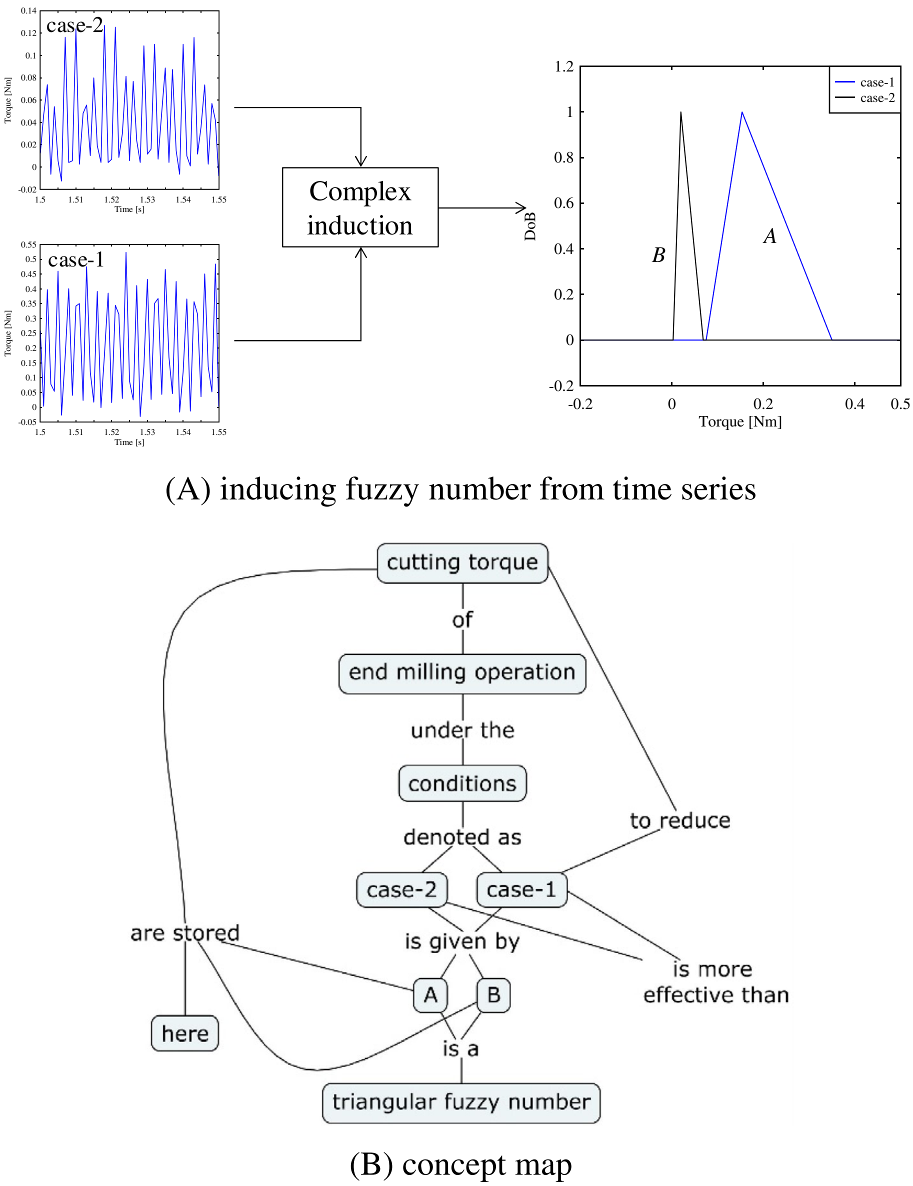


FIGURE 5 Complex induction-based knowledge

cutting conditions referred to as case-1 and case-2. Numerous methods can be used to induce a fuzzy number from a given set of time-series numerical data.[81,82] Such induction is a complex process requiring all types and categories of knowledge. Thus, if fuzzy numbers in Figure 5A are considered knowledge provenance, some pieces of knowledge represented by the concept map in Figure 5B qualify as complex-induction-based knowledge. The concept map in Figure 5B boils down to the following statements:

(1) Cutting torque of end-milling operation in case-1 is denoted as A.
(2) Cutting torque of end-milling operation in case-2 is denoted by B.
(3) A is a triangular fuzzy number.
(4) B is a triangular fuzzy number.
(5) Case-2 is more effective at reducing cutting torque compared to case-1.
(6) Cutting torques A and B are stored "here."

The first two statements represent two pieces of complex-induction-based knowledge since a complex computational-intelligence-based procedure underlies the induction of A and B. Statements (3) and (4) qualify as the pieces of definitional knowledge. Whereas statement (5) represents informal-induction-based knowledge that evolves from visual inspection of relative positions of A and B. The last statement is a piece of information (not knowledge) that directs a user to the provenance, that is, data sources relevant to Figure 5A. This example demonstrates that different types and categories of knowledge constitute a concept map, and some segments need not necessarily be a piece of knowledge.

4.4 | Creative knowledge

Unlike deductive and inductive knowledge, creative knowledge does not rely on knowledge provenance. It provides plausible explanations/solutions to an issue. This, in some cases, might lead to controversies. Creative knowledge exists in three categories—analytic a priori-based, synthetic a priori-based, and synthetic a posteriori-based—described as follows.

Let us first consider analytic a priori-based creative knowledge. As the name suggests, this category of knowledge is introduced by an individual to define certain concepts; however, the definitions can be considered false or true depending on the personal preference of others. This implies that some may consider the definitions to be true, whereas others may not. For example, consider the concept map depicted in Figure 6. It boils down to the following statements:

(1) A product attribute means an attractive attribute, reverse attribute, indifferent attribute, must-be attribute, or one-dimensional attribute.
(2) Presence of an attractive attribute contributes to customer satisfaction.
(3) Absence of attractive attribute does not contribute to customer dissatisfaction.

The first statement is a piece of analytic a priori-based creative knowledge. The reason is as follows. Here, statement (1) classifies product attributes into five types.[83,84] Other researchers may define product attributes in other ways. Consequently, this statement may be true for some product developers and false or partially true for others. On the other hand, statements (2) and (3) do not qualify as pieces of analytic-a priori-based creative knowledge because these statements collectively define the nature of the attractive attribute exclusively. Thus, statements (2) and (3) represent definitional knowledge. Besides the abovementioned example, consider the following statements to further understand the analytic-a priori-based creative knowledge.

(1) "Fundamental human needs demonstrate a hierarchy, and they can be classified in the ascending order as—physiological needs, safety needs, social belonging, self-esteem, and self-actualization".

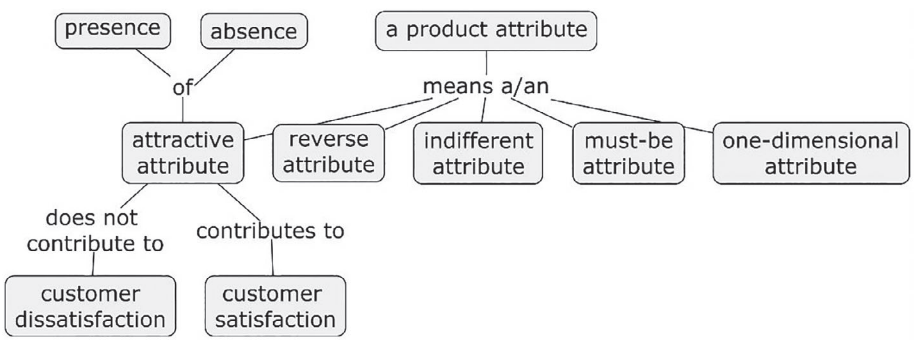


FIGURE 6 Example of analytic a priori-based creative knowledge

(2) “Fundamental human needs are nonhierarchical, and they can be classified as subsistence, protection, affection, understanding, participation, leisure, creation, identity, and freedom.”

Both statements define human needs in two different ways. Therefore, both represent pieces of analytic-a priori-based creative knowledge. The former statement was proposed by Maslow.[85,86] whereas the latter was proposed by Max-Neef.[87-89] If someone attempts another definition of human needs will be created. However, its category would remain unchanged—analytic-a priori-based creative knowledge. Thus, the definition of knowledge presented in Section 3 boils down to some pieces of analytic-a priori-based creative knowledge.

Let us now consider synthetic-a priori-based creative knowledge. Here, a new concept or parameter is injected to establish a relationship among existing concepts/parameters using deduction. A classic example of synthetic-a priori-based creative knowledge is presented by the concept map depicted in Figure 7. It boils down to the following statements:

(1) Euler's number e can be expressed as $e^x = 1 + (x/1!) + (x^2/2!) + (x^3/3!) + \ldots$

(2) Sine function can be expressed as $\sin(x) = x - ((x^3)/(3!)) + ((x^5)/(5!)) - ((x^7)/(7!)) + \ldots$

(3) Cosine function can be expressed as $\cos(x) = 1- ((x^2)/(2!)) + ((x^4)/(4!)) - ((x^6)/(6!)) + \ldots$

(4) Functions e^x, $\sin(x)$, and $\cos(x)$ yield $e^{ix} = \cos(x) + i{*}\sin(x)$, wherein “$i$” equals the square root of -1, that is, $i = \sqrt{-1}$.

(5) An imaginary number can be represented using $i = \sqrt{-1}$.

(6) The relation $e^{ix} = \cos(x) + i{*}\sin(x)$ yields $e^{i\pi} + 1 = 0$ if $x = \pi$ ($pi = \pi$).

(7) Euler's identity implied $e^{i\pi} + 1 = 0$.

The first three statements represent pieces of knowledge classified as secondary relations of ideas because these can be derived via deduction from respective primary relations of ideas and definitional knowledge. For the same reason, statement (6) is also a secondary relation of ideas. Statements (5) and (7) are pieces of definitional knowledge, whereas statement (4) is a piece of synthetic-a priori-based creative knowledge since it entails a new concept (imaginary number $i = \sqrt{-1}$) that was not known before Euler introduced it to deduce a relationship between the Euler's number, sine function, and cosine function. Remarkably, synthetic-a priori-based creative knowledge has a temporal dimension. As a result, it may transform into definitional knowledge at a later time. For example, nowadays, an imaginary number is a piece of definition knowledge. At the time of its inception, it was a piece of synthetic a priori-based creative knowledge.

Finally, let us consider synthetic-a posteriori-based creative knowledge. This category includes pieces of knowledge that emerge owing to pragmatic preferences, which are led by data- or experience-driven activities. For example, consider a signal (time series) that provides information about surface heights of an arbitrary machined surface, as depicted in Figure 8A. A concept map gives some pieces of knowledge underlying the signal, depicted in Figure 8B, which boils down to the following statements.

(1) A signal (time series) may comprise three stochastic features—trends, noises, and bursts.

(2) The stochastic features can be defined using functions T, N, and B, respectively.

(3) Functions T, N, and B can be added to yield function S given by $S = T + N + B$.

(4) S can be used to simulate signals (time series).

The first statement is an example of synthetic-a-posteriori-based creative knowledge because it seems (to an individual) that the given signal (Figure 8A) is caused by the stochastic features (trends, noises, and bursts); other individuals might imagine it differently. The second and third statements represent the pieces of definitional knowledge. On the other

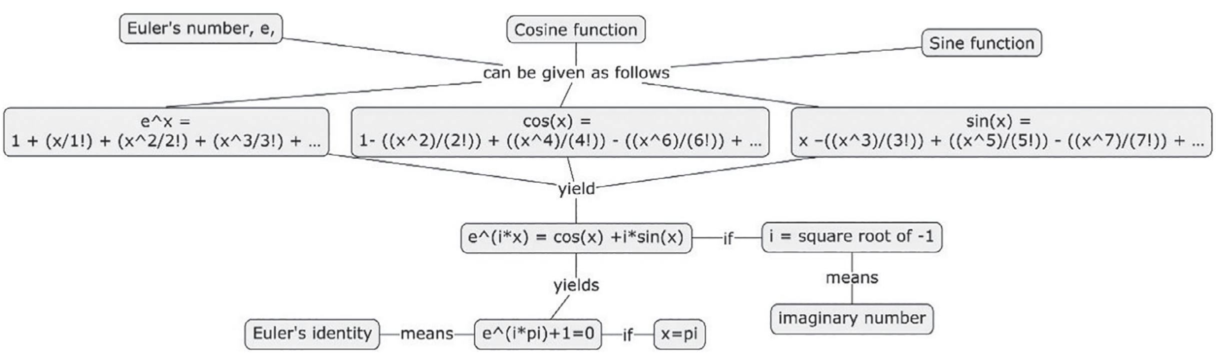
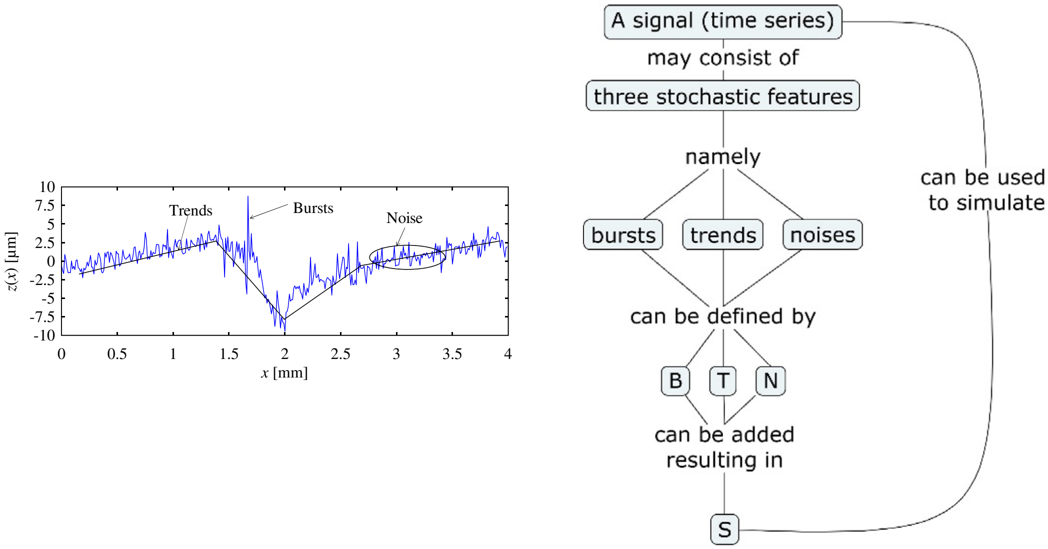


FIGURE 7 Example of synthetic a priori-based creative knowledge



(A) a signal (B) a concept map

FIGURE 8 Example of synthetic a posteriori-based creative knowledge

hand, the last statement is a piece of analytic-a priori-based creative knowledge since it is unclear whether or not signals can be accurately simulated by the function *S*.

5 | DISCUSSIONS

As described in Sections 3 and 4, the different types and categories of knowledge tend to coexist, except definitional knowledge. Knowledge representation can be performed using knowledge-type-aware concept mapping, wherein the types and categories of knowledge play a vital role. It is worth mentioning that when a concept map represents a piece of knowledge claim, it may incorporate other relevant content, such as those relevant to knowledge provenance. At the same time, other nonknowledge contents (eg, information to help users grasp the meaning of the concept map) may also be considered part of a concept map. In order to understand this issue in greater detail, a creative design process has been considered and represented by a concept map of a solid-fuel-based engine developed for Mars exploration.[42,43,90]

Figure 9 depicts seven interdependent concept maps, denoted by C1, … ,C7, that collectively represent the solid-fuel-based engine's conceptual design. For the sake of analysis, internal combustion (IC) engines are considered to be available in the market a priori. The same, however, is not valid for solid-fuel-based engines. Consider the concept map (C1) that boils down to the proposition that an IC engine requires a fuel and an oxidizer. This is the definition of an IC engine, and, therefore, represents a piece of definitional (or analytic a priori) knowledge. The second concept map (C2) boils down to the proposition that the earth's atmosphere supplies ample O_2 (>20%) and hydrocarbons, but hardly supplies any CO_2 (<0.05%). This is a piece of informal-induction-based knowledge. Experimental data regarding chemical analyses of the substances found in the earth atmosphere form the knowledge provenance for this piece of knowledge. The third concept map (C3) boils down to the statement that an IC engine uses O_2 as an oxidizer and hydrocarbons as a fuel. This qualifies as informal-induction-based knowledge, and data regarding oxidizers and fuels used of existing IC engines form the provenance for this piece of knowledge. Concept map (C4) boils down to the statement that an ample supply of fuel and oxidizer is essential for an IC engine. This, too, qualifies as a piece of informal-induction-based knowledge for which data concerning the performance of the existing IC engine constitutes knowledge provenance. Up to C4, the design process deals with the existing IC engine. From C5 onward, the focus is shifted to a new engine that usages Magnesium (Mg) as a solid fuel. The fifth concept map (C5) boils down to the proposition that the engine for Mars exploration may require fuel and an oxidizer. This is an analytic-a priori-based creative knowledge. No knowledge provenance (data or theoretical analysis) is available to support this proposition; it is neither true nor false at the time of its conception. The sixth concept map (C6) boils down to the statement that Mars'

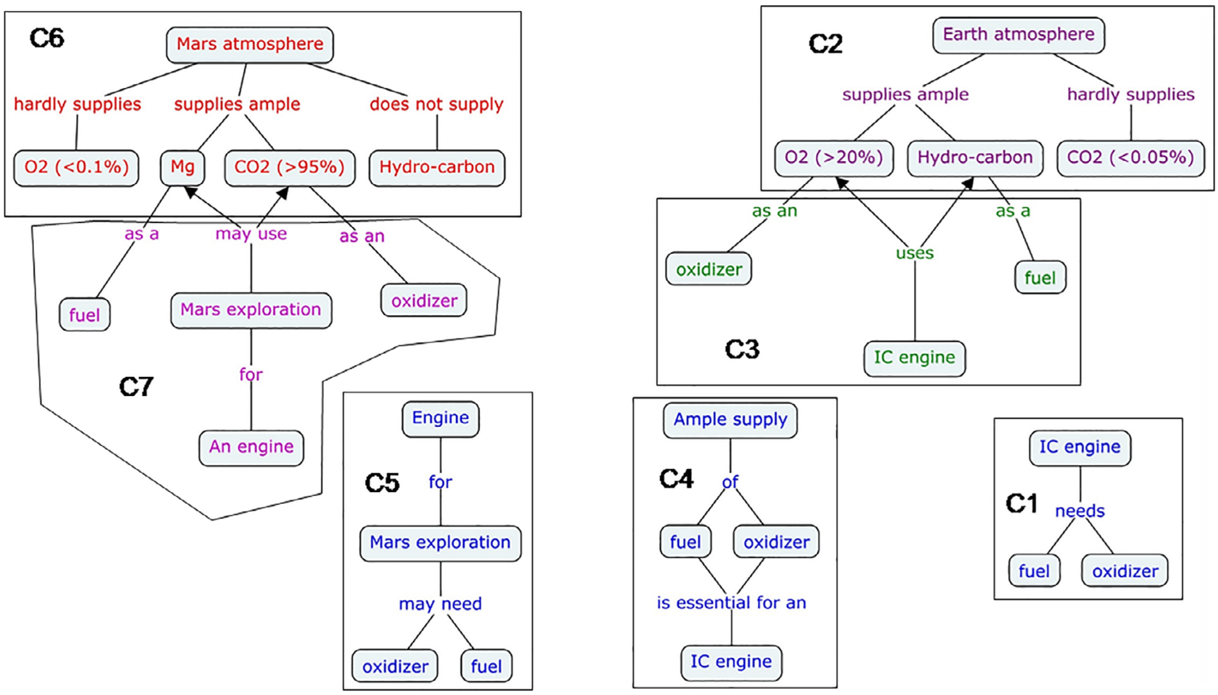


FIGURE 9 Knowledge-type-aware analysis of a creative design process

atmosphere supplies ample Mg, CO_2 (>95%), hardly supplies any O_2 (<0.1%), and does not supply hydrocarbons. This is a piece of informal-induction-based knowledge, and experimental data obtained from chemical analyses of substances found within Mars' atmosphere form the provenance for this knowledge. The last concept map (C7) boils down to the proposition that an engine for Mars exploration may use Mg as fuel and CO_2 as an oxidizer. This represents analytic-a priori-based creative knowledge since no knowledge provenance (data or theoretical analysis) is available to support this proposition at the time of its inception. Thus, it is neither true nor false. This piece of knowledge, in turn, leads the design process of solid-fuel-based engines for Mars' exploration into the embodiment, parametric, and detailed design stages, respectively.

It is clear from the characteristics of concept maps C1, … , C7 that a creative design process entails definitional knowledge, analytic-a priori-based creative knowledge, and informal-induction-based knowledge. Formal computation-based knowledge (eg, secondary relations of ideas, complex induction-based knowledge, and synthetic a posteriori-based knowledge) hardly dominates a creative design process. This is perhaps a characteristic of creative design processes. Similar investigations can be performed to determine the characteristics of other design processes, such as embodiment design, parametric design, and detailed design. Thus, a more comprehensive and systematic structure of each design process can be established. In turn, this would help digitize knowledge-intensive activities more effectively from both human and machine-learning viewpoints. The same augment is valid for knowledge-intensive activities relevant to manufacturing. As a result, knowledge-type-aware concept mapping activities can benefit engineering design and manufacturing as well as engineering informatics.

The findings discussed thus far in this article refer to the scenario schematically illustrated in Figure 10. As can be seen in Figure 10, five integrated domains denoted by D1, … , D5 must work collectively to realize the engineering informatics objectives relevant to Industry 4.0. The first domain (D1) records the previously performed operational, analytical, and creative activities. These activities refer to knowledge claim, provenance, and inference that help create the domain denoted as D2. D2 must be integrated with D3, which can organize elements of knowledge into knowledge-type-aware concept maps, to facilitate human and machine learnings. D4 is populated with the outcomes of D3. Thus, it represents a set of knowledge-type-aware concept maps. Contents of D4 are fed into D5, the domain of smart manufacturing, wherein the distributed embedded systems (cyberphysical systems, digital twins, and IoT-embedded manufacturing enablers [such as machine tools, robots, and material handling devices]) function. Research endeavors explicitly aimed at addressing the construction of these domains would offer benefits to smart manufacturing techniques. In doing so, the types and categories of knowledge presented in this article will play a pivotal role.

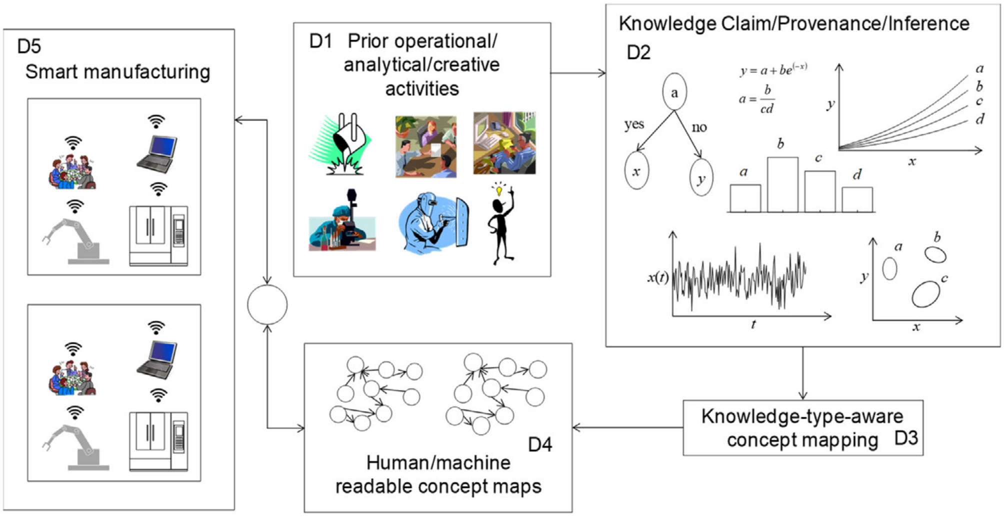


FIGURE 10 Knowledge-type-aware informatics for Industry 4.0

The cognitive task-based autonomous agents that materialize Industry 4.0 (IIoT, cyberphysical systems, and digital twins) are always subjected to cyber risk. Radanliev et al[91] have introduced an epistemological framework of standardizing cyber risk and decision-making, avoiding such risks. The kind of framework must be integrated with the abovementioned knowledge-type-aware informatics, ensuring the robustness of the agents. Since both the cyber risk framework[91] and knowledge-type-aware informatics are based on epistemological considerations, the integration may not be difficult to achieve. This issue remains open for further research.

The role of human resources has been redefined in Industry 4.0, where workers are supposed to engage in more cognitive tasks, and easing of physical tasks must be enhanced using advanced ergonomic arrangements.[92] Thus, empowering human resources with the required knowledge has become an important issue. In this respect, various computer-aided human learning concepts have been introduced (eg, Education 4.0, Operator 4.0, and alike).[93-95] For example, in Operator 4.0, adaptive learning at work, sharing knowledge, collaborative job design, adaptive solution making must go hand in hand.[93] A similar trend is observed in the case of Education 4.0, with an emphasis on augmented-reality-based educational content. The knowledge-type-aware contents can be used while building the systems that empower human resources under the umbrella of Education 4.0 or Operator 4.0. This will make the learning system development process, as well as learning outcome assessment process, more focused and productive. Further study can be carried out in this direction.

Industry 4.0 underlies a complex ecosystem. In this ecosystem, manufacturing enablers (eg, CAD/CAM systems, monitoring systems, material handling systems, programmable machines and tools, robots, and human resources) make myriad proximal and distal interactions among the cyberphysical systems, IIoT, cloud computing, and digital twins. These interactions are supposed to make the manufacturing enablers autonomous in solving problems and performing high-level cognitive tasks (understand, predict, decide, act, and adapt). Now, solving a problem or performing a cognitive task requires knowledge. If it (solving a problem or performing a cognitive task) is done in the Industry 4.0 ecosystem, digitized knowledge is required. Therefore, digitize knowledge is critical to the Industry 4.0 ecosystem. The remarkable thing is that knowledge entails another complex ecosystem defined as a knowledge ecosystem. In this ecosystem, knowledge makes myriad proximal and distal interactions among human learning, machine learning, logical inferences (deduction, induction, and abduction), experimental data, analytical results, simulations, algorithms, creative thinking, and cognitive reflections. The outcomes of this study bridge the gap between these ecosystems (Industry 4.0 ecosystem and knowledge ecosystem). Thus, this study establishes the fundamentals based on which sophisticated methods and tools can be developed for the advancement of Industry 4.0.

6 | CONCLUDING REMARKS

Without apply digitized knowledge, problems cannot be solved in Industry 4.0. Thus, any ambiguity in the definition of knowledge creates unnecessary complexity and hinders the advancement of Industry 4.0.

As found from the articulations of knowledge reported in the extant literature of epistemology, engineering design, manufacturing, organization science, information science, and education science, most authors attempting to define knowledge have restricted themselves to their respective disciplines and provided piecemeal solutions. Some of the definitions suffer circularity. Notably, the concepts such as human learning, machine learning, logical inferences (deduction, induction, and abduction), experimental data, analytical results, simulations, algorithms, creative thinking, cognitive reflections, virtue, and moral thinking, have been the leading causes of circularity. Thus, eliminating circularity (ie, straightforwardly positioning knowledge to the abovementioned concepts) in the definition of knowledge as well as maintaining a genial attitude toward all definitions reported to date constitutes a significant challenge when attempting to define knowledge. This article overcomes this challenge by introducing a three-element-based definition of knowledge, that is, a piece of knowledge consists of knowledge claim, knowledge provenance, and knowledge inference. These elements have been defined in clear terms to help distinguish between knowledge and data/information. Knowledge inference helps define knowledge types—definitional, deductive, inductive, or creative—whereas knowledge claim manifests knowledge in explicit terms. Each type of knowledge exhibits some categories, which have been exemplified using real-life scenarios relevant to engineering design and manufacturing. It has been observed that no other knowledge types or categories can exist independently except definitional knowledge. However, they form concept maps (user-defined ontologies), which are networks of concepts forming a knowledge graph. These graphs can easily be digitized to make them available to the relevant systems using semantic web technology. In other words, when a piece of knowledge is studied, its contents boil down to definitional, deductive, inductive, and/or creative knowledge.

Consequently, when constructing knowledge graphs for human or machine learning, contents can be organized and analyzed based on the type of knowledge and its categories. This way, the types of categories of knowledge can be used as semantic annotations, making them distinguishable from other relevant contents such as experimental data, analytical results, simulations, algorithms, creative thinking, and alike. Thus, if the outcomes of this study are utilized in developing cyberphysical systems, unnecessary computational complexity can be avoided and the systems become transparent and manageable due to semantic richness.

Nevertheless, defining knowledge implies proposing pieces of analytic a priori-based creative knowledge. Thus, the process of defining knowledge requires further development. In this sense, the proposed study marks the beginning of a long journey that would end when the definition of knowledge becomes an analytic a priori knowledge to all stakeholders.

PEER REVIEW INFORMATION

Engineering Reports thanks the anonymous reviewers for their contribution to the peer review of this work.

CONFLICT OF INTEREST

The author has no conflict of interest relevant to this article.

ORCID

AMM Sharif Ullah https://orcid.org/0000-0003-4584-5288

REFERENCES

1. de Weck OL. Systems engineering 20th anniversary special issue. *Syst Eng*. 2018;21(3):143-147. https://doi.org/10.1002/sys.21443.
2. Tomiyama T, Smith IFC, Chen C-H, O'Brien W. Editorial. *Adv Eng Inform*. 2012;26(1):1-2. https://doi.org/10.1016/j.aei.2011.11.002.
3. Veile Johannes W, Kiel D, Müller Julian M, Voigt K-I. Lessons learned from industry 4.0 implementation in the German manufacturing industry. *J Manuf Technol Manag*. 2019. https://doi.org/10.1108/JMTM-08-2018-0270.
4. Ghobakhloo M. The future of manufacturing industry: a strategic roadmap toward industry 4.0. *J Manuf Technol Manag*. 2018;29(6):910-936. https://doi.org/10.1108/JMTM-02-2018-0057.
5. Raptis TP, Passarella A, Conti M. Data management in industry 4.0: state of the art and open challenges. *IEEE Access*. 2019;7:97052-97093. https://doi.org/10.1109/ACCESS.2019.2929296.
6. Ansari F. Knowledge management 4.0: theoretical and practical considerations in cyber physical production systems. *IFAC-PapersOnLine*. 2019;52(13):1597-1602. https://doi.org/10.1016/j.ifacol.2019.11.428.
7. Sharif Ullah AMM. Modeling and simulation of complex manufacturing phenomena using sensor signals from the perspective of Industry 4.0. *Advanced Engineering Informatics*. 2019;39:1-13. http://dx.doi.org/10.1016/j.aei.2018.11.003.
8. Zhou Ji, Li Peigen, Zhou Yanhong, Wang Baicun, Zang Jiyuan, Meng Liu. Toward New-Generation Intelligent Manufacturing. *Engineering*. 2018;4(1):11-20. http://dx.doi.org/10.1016/j.eng.2018.01.002.
9. Feng Shaw C, Bernstein William Z, Hedberg Thomas, Barnard Feeney Allison. Toward Knowledge Management for Smart Manufacturing. *Journal of Computing and Information Science in Engineering*. 2017;17(3):http://dx.doi.org/10.1115/1.4037178.
10. Sinclair Murray, Siemieniuch Carys, Palmer Paul. The identification of knowledge gaps in the technologies of cyber-physical systems with recommendations for closing these gaps. *Systems Engineering*. 2019;22(1):3-19. http://dx.doi.org/10.1002/sys.21464.

11. Gao James, Nee Andrew YC. An overview of manufacturing knowledge sharing in the product development process. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*. 2018;232(13):2253-2263. http://dx.doi.org/10.1177/0954405418759375.
12. Souri Mohammed El, Gao James, Simmonds Clive. Integrating Manufacturing Knowledge with Design Process to Improve Quality in the Aerospace Industry. *Procedia CIRP*. 2019;84:374-379. http://dx.doi.org/10.1016/j.procir.2019.04.179.
13. PompAndré, Paulus Alexander, Kirmse Andreas, Kraus Vadim, Meisen Tobias. Applying Semantics to Reduce the Time to Analytics within Complex Heterogeneous Infrastructures. *Technologies*. 2018;6(3):86. http://dx.doi.org/10.3390/technologies6030086.
14. Paulus D, Pomp A, Poth L, Lipp J, Meisen T. Current and future industry Recommending Semantic Concepts for Improving the Process of Semantic Modeling. *Enterprise Information Systems. ICEIS 2018.* Lecture Notes in Business Information Processing 363. Cham: Springer; 2019. https://doi.org/10.1007/978-3-030-26169-6_17.
15. Chhim Peter, Chinnam Ratna Babu, Sadawi Noureddin. Product design and manufacturing process based ontology for manufacturing knowledge reuse. *Journal of Intelligent Manufacturing*. 2019;30(2):905-916. http://dx.doi.org/10.1007/s10845-016-1290-2.
16. Li Dan, Fast-Berglund Åsa, Paulin Dan. Current and future Industry 4.0 capabilities for information and knowledge sharing. *The International Journal of Advanced Manufacturing Technology*. 2019;105(9):3951-3963. http://dx.doi.org/10.1007/s00170-019-03942-5.
17. Gettier E. L. Is Justified True Belief Knowledge?. *Analysis*. 1963;23(6):121-123. http://dx.doi.org/10.1093/analys/23.6.121.
18. N N. (Last accessed, 2019.08.14); 2019. https://www.collinsdictionary.com/dictionary/english/knowledge.
19. Abele Eberhard, Chryssolouris George, Sihn Wilfried, Metternich Joachim, ElMaraghy Hoda, Seliger Günther, Sivard Gunilla, ElMaraghy Waguih, Hummel Vera, Tisch Michael, Seifermann Stefan. Learning factories for future oriented research and education in manufacturing. *CIRP Annals*. 2017;66(2):803-826. http://dx.doi.org/10.1016/j.cirp.2017.05.005.
20. Zagzebski L. What is Knowledge?. *J. Greco & E. Sosa (Eds.), The Blackwell Guide to Epistemology (pp. 92-116)*. Oxford: Blackwell; 2017:92-116. https://doi.org/10.1002/9781405164863.ch3.
21. Sosa, E. *Epistomology*. Princeton: New Jersey; 2018.
22. Steup, M. Epistemology. N. Zalta Edward (ed.), *The Stanford Encyclopedia of Philosophy (Fall 2017 Edition)*. Stanford, CA: Metaphysics Laboratory, Stanford University; 2018. https://plato.stanford.edu/archives/fall2017/entries/scientific-explanation/. Accessed May 9, 2019.
23. Hempel Carl G. Maximal Specificity and Lawlikeness in Probabilistic Explanation. *Philosophy of Science*. 1968;35(2):116-133. http://dx.doi.org/10.1086/288197.
24. Salmon W.C, Jeffrey R.C, Greeno J.G. Statistical Explanation and Statistical Relevance. Pittsburgh, PA: University of Pittsburgh Press; 1971.
25. Shrader, Douglas W. Causation, Explanation, and Statistical Relevance. *Philosophy of Science*. 1977;44(1):136-145. http://dx.doi.org/10.1086/288729.
26. Salmon W. Statistical Explanation. Salmon W, *Statistical Explanation and Statistical Relevance*. Pittsburgh, PA: University Pittsburgh Press; 1971:29-88. https://doi.org/10.2307/j.ctt6wrd9p.6.
27. Salmon W.C. *Four Decades of Scientific Explanation*. Pittsburgh, PA: University of Pittsburgh Press; 2006. https://doi.org/10.2307/j.ctt5vkdm7, https://doi.org/10.4324/0123456789-P072-1.
28. Woodward J. Scientific Explanation. Edward N. Zalta, *The Stanford Encyclopedia of Philosophy (Fall 2017 Edition)*. 2017. https://plato.stanford.edu/archives/fall2017/entries/scientific-explanation.
29. Locke J, Berkeley G, Hume D, eds. *The Empiricists. John Locke: An essay concerning human understanding, abridged by Richard Taylor. George Berkeley: A treatise concerning the principles of human knowledge. Three dialogues between Hylas and Philonous, in opposition to sceptics and atheists. David Hume: An enquiry concerning human understanding. Dialogues concerning natural religion*. Garden City, NY: Anchor Press; 1960, 1989:51-61.
30. Kant I. Guyen P, Wood A.W, *Critique of Pure Reason: The Cambridge Edition of the Works of Immanuel Kant*. 1998.
31. Russell Bertrand V—Knowledge by Acquaintance and Knowledge by Description. *Proceedings of the Aristotelian Society*. 2015;11(1):108-128. http://dx.doi.org/10.1093/aristotelian/11.1.108.
32. Russell B. *Our Knowledge of the External World*. London: The Open Court Publishing Company; 1914.
33. BonJour L. A Version of Internalist Foundationalism, BonJour L Sosa E, eds. *Epistemic Justification: Internalism vs. Externalism, Foundationalism vs. Virtue*. Malden, MA: Blackwell; 2003.
34. Fumerton Richard. Speckled Hens and Objects of Acquaintance. *Philosophical Perspectives*. 2005;19(1):121-138. http://dx.doi.org/10.1111/j.1520-8583.2005.00056.x.
35. Battaly H. et al. Intellectual Virtue. *The Routledge Encyclopedia of Philosophy*. UK: Taylor and Francis; 2018. https://www.rep.routledge.com/articles/thematic/intellectual-virtue/v-1.doi:10.4324/0123456789-P072-1.
36. Greco John. Virtues and Vices of Virtue Epistemology. *Canadian Journal of Philosophy*. 1993;23(3):413-432. http://dx.doi.org/10.1080/00455091.1993.10717329.
37. Tomiyama T, Takeda H, Yoshioka M, Shimomura Y. Abduction for Creative Design. *Proceedings of the 15th International Conference on Design Theory and Methodology*. ASME; 2003:ASME International Design Engineering Technical Conferences and Computers and Information in Engineering Conference; 3(b):543-552. https://doi.org/10.1115/DETC2003/DTM-48650.
38. Yoshikawa H. General Design Theory and a CAD System. Sata T, Warman E. *Proceedings of the IFIP WG 5.2, 5.3, Working Conference 1980 (Tokyo)*. Man-Machine Communication in CAD/CAM Amsterdam: North-Holland Publishing; 1981.35-57.
39. Yoshikawa H. General Design Theory as a Formal Theory of Design. Yoshikawa H, Gossard D, *Intelligent CAD I*. Amsterdam: North-Holland Publishing; 1989;32(1):51-61.
40. Reich Yoram. A critical review of General Design Theory. *Research in Engineering Design*. 1995;7(1):1-18. http://dx.doi.org/10.1007/bf01681909.

41. Takeda H, Veerkamp P, Tomiyama T, Yoshikawa H. Modeling Design Process. *AI Magazine*. 1990;11(4):37-48. https://doi.org/10.1609/aimag.v11i4.855.
42. Hatchuel Armand, Weil Benoit. C-K design theory: an advanced formulation. *Research in Engineering Design*. 2009;19(4):181-192. http://dx.doi.org/10.1007/s00163-008-0043-4.
43. Sharif Ullah A.M.M, Rashid Md. Mamunur, Tamaki Jun'ichi. On some unique features of C–K theory of design. *CIRP Journal of Manufacturing Science and Technology*. 2012;5(1):55-66. http://dx.doi.org/10.1016/j.cirpj.2011.09.001.
44. Agogue M, Kazakci A. 10 Years of C–K Theory: A Survey on the Academic and Industrial Impacts of a Design Theory. Chakrabarti A, Blessing L, *An Anthology of Theories and Models of Design*. London: Springer; 2014:219-235. https://doi.org/10.1007/978-1-4471-6338-1_11.
45. Le Masson P, Weil B, Hatchuel A. In: Michie D, ed. *Design Theory Methods and Organization for Innovation*. Gewerbestrasse, Cham: Springer International Publishing; 2017.
46. Ullah A.M.M. Sharif. Logical interaction between domain knowledge and human cognition in design. *International Journal of Manufacturing Technology and Management*. 2008;14(1/2):215-227. http://dx.doi.org/10.1504/ijmtm.2008.017496.
47. Ghosh Angkush Kumar, Ullah AMM Sharif, Kubo Akihiko. Hidden Markov model-based digital twin construction for futuristic manufacturing systems. *Artificial Intelligence for Engineering Design, Analysis and Manufacturing*. 2019;33(03):317-331. http://dx.doi.org/10.1017/s089006041900012x.
48. Zheng Pai, wang Honghui, Sang Zhiqian, Zhong Ray Y, Liu Yongkui, Liu Chao, Mubarok Khamdi, Yu Shiqiang, Xu Xun. Smart manufacturing systems for Industry 4.0: Conceptual framework, scenarios, and future perspectives. *Frontiers of Mechanical Engineering*. 2018;13(2):137-150. http://dx.doi.org/10.1007/s11465-018-0499-5.
49. Polanyi M, Nye M.J. *Personal Knowledge: Towards a post-critical philosophy*. Chicago, IL: The University of Chicago Press; 2015. https://doi.org/10.1007/BF00994016.
50. Nonaka Ikujiro. A Dynamic Theory of Organizational Knowledge Creation. *Organization Science*. 1994;5(1):14-37. http://dx.doi.org/10.1287/orsc.5.1.14.
51. Nonaka I, Takeuchi H. *The knowledge-creating company: How Japanese companies create the dynamics of innovation*. New York: Oxford University Press; 1995.
52. Nonaka Ikujiro, Kodama Mitsuru, Hirose Ayano, Kohlbacher Florian. Dynamic fractal organizations for promoting knowledge-based transformation – A new paradigm for organizational theory. *European Management Journal*. 2014;32(1):137-146. http://dx.doi.org/10.1016/j.emj.2013.02.003.
53. Randles Theodore J, Blades Christopher D, Fadlalla Adam. The Knowledge Spectrum. *International Journal of Knowledge Management*. 2012;8(2):65-78. http://dx.doi.org/10.4018/jkm.2012040104.
54. Albino V, Garavelli A.C, Schiuma G. A metric for measuring knowledge codification in organisation learning. *Technovation*. 2001;21(7):413-422. http://dx.doi.org/10.1016/s0166-4972(00)00058-4.
55. Bohn R. Measuring and Managing Technological Knowledge. *Sloan management review*. 1994.36(1):61-73. http://dx.doi.org/10.1016/B978-0-7506-7009-8.50022-7.
56. Carson Robert N. A Taxonomy of Knowledge Types for Use in Curriculum Design. *Interchange*. 2004;35(1):59-79. http://dx.doi.org/10.1023/b:inch.0000039020.49283.90.
57. Kinchin Ian M, Möllits Aet, Reiska Priit. Uncovering Types of Knowledge in Concept Maps. *Education Sciences*. 2019;9(2):131. http://dx.doi.org/10.3390/educsci9020131.
58. Ullah AMM Sharif. Fundamental Issues of Concept Mapping Relevant to Discipline-Based Education: A Perspective of Manufacturing Engineering. *Education Sciences*. 2019;9(3):228. http://dx.doi.org/10.3390/educsci9030228.
59. Quinlan J.R. Discovering Rules by Induction from Large Collection of Example. Michie D. *Expert Systems in the Micro-Electronic Age*. Edinburgh: Edinburgh University Press; 1979.
60. Hayes-Roth F, Waterman D.A, Lenat D.B. *Building Expert Systems*. Reading, MA: Addision-Wesley; 1987.
61. Quinlan J. R. Induction of decision trees. *Machine Learning*. 1986;1(1):81-106. http://dx.doi.org/10.1007/bf00116251.
62. Nagao M. *Knowledge and Inference*. New York: Academic Press; 1990.
63. Heckerman David, Geiger Dan, Chickering David M. Learning Bayesian networks: The combination of knowledge and statistical data. *Machine Learning*. 1995;20(3):197-243. http://dx.doi.org/10.1007/bf00994016.
64. Studer Rudi, Benjamins V. Richard, Fensel Dieter. Knowledge engineering: Principles and methods. *Data & Knowledge Engineering*. 1998;25(1-2):161-197. http://dx.doi.org/10.1016/s0169-023x(97)00056-6.
65. Rathnam Chandramouli, Lee Sanghoon, Jiang Xia. An algorithm for direct causal learning of influences on patient outcomes. *Artificial Intelligence in Medicine*. 2017;75:1-15. http://dx.doi.org/10.1016/j.artmed.2016.10.003.
66. Zadesh L.A. Some Reflections on Information Granulation and its Centrality in Granular Computing, Computing with Words, the Computational Theory of Perceptions and Precisiated Natural Language. Lin T.Y, Yao Y.Y, Zadeh L.A, *Data Mining, Rough Sets and Granular Computing*. Heidelberg: Physica-Verlag HD; 2002.3-20.
67. Ullah A.M.M. Sharif, Harib Khalifa H. A human-assisted knowledge extraction method for machining operations. *Advanced Engineering Informatics*. 2006;20(4):335-350. http://dx.doi.org/10.1016/j.aei.2006.07.004.
68. Mizzaro S. Towards a theory of epistemic information, eds. *Information Modelling and Knowledge Bases*. Amsterdam: IOS Press; 2001.
69. Ausubel D, Novak J, Hanesian H. *Educational psychology: a cognitive view (2nd ed.)*. New York: Holt, Rinehart & Winston; 1978.
70. Ausubel D.P, et al. *The acquisition and retention of knowledge: A cognitive view*. Dordrecht, The Netherlands: Kluwer Academic Publishers; 2000.

71. Novak J.D. *Learning, creating, and using knowledge: Concept maps as facilitative tools in schools and corporations (2nd ed.)*. New York: Rutledge; 2012:105644.
72. Ullah AMM Sharif. On the interplay of manufacturing engineering education and e-learning. *International Journal of Mechanical Engineering Education*. 2016;44(3):233-254. http://dx.doi.org/10.1177/0306419016651948.
73. Seel N.M. Assimilation Theory of Learning. Seel N.M, *Encyclopedia of the Sciences of Learning*. Boston, MA: Springer; 2012. https://doi.org/10.1016/j.promfg.2018.04.005.
74. Fionda Valeria, Pirrò Giuseppe, Consens Mariano P. Querying knowledge graphs with extended property paths. *Semantic Web*. 2019;10(6):1127-1168. http://dx.doi.org/10.3233/sw-190365.
75. Kim Haklae. Towards a sales assistant using a product knowledge graph. *Journal of Web Semantics*. 2017;46-47:14-19. http://dx.doi.org/10.1016/j.websem.2017.03.001.
76. Mordecai Yaniv, Dori Dov. Minding the Cyber-Physical Gap: Model-Based Analysis and Mitigation of Systemic Perception-Induced Failure. *Sensors*. 2017;17(7):1644. http://dx.doi.org/10.3390/s17071644.
77. Mordecai Yaniv. Model-based protocol specification. *Systems Engineering*. 2019;22(2):188-210. http://dx.doi.org/10.1002/sys.21480.
78. Chen Ruirui, Liu Yusheng, Zhao Jianjun, Ye Xiaoping. Model verification for system design of complex mechatronic products. *Systems Engineering*. 2019;22(2):156-171. http://dx.doi.org/10.1002/sys.21470.
79. Ullah AMM Sharif. Machining Forces Due to Turning of Bimetallic Objects Made of Aluminum, Titanium, Cast Iron, and Mild/Stainless Steel. *Journal of Manufacturing and Materials Processing*. 2018;2(4):68. http://dx.doi.org/10.3390/jmmp2040068.
80. Ullah A.M.M. Sharif, D'Addona Doriana, Arai Nobuyuki. DNA based computing for understanding complex shapes. *Biosystems*. 2014;117:40-53. http://dx.doi.org/10.1016/j.biosystems.2014.01.003.
81. Masson Marie-Hélène, Denœux Thierry. Inferring a possibility distribution from empirical data. *Fuzzy Sets and Systems*. 2006;157(3):319-340. http://dx.doi.org/10.1016/j.fss.2005.07.007.
82. Sharif Ullah A M M, Shamsuzzaman M. Fuzzy Monte Carlo Simulation using point-cloud-based probability–possibility transformation. *SIMULATION*. 2013;89(7):860-875. http://dx.doi.org/10.1177/0037549713482174.
83. Kano N, Seraku N, Takahashi F, Tsuji S. Attractive Quality and Must-be Quality. *Journal of The Japan Society for Quality Control*. 1984;14(2):147-156. https://doi.org/10.20684/quality.14.2_147.
84. Sharif Ullah A. M. M, Tamaki Jun'ichi. Analysis of Kano-model-based customer needs for product development. *Systems Engineering*. 2011;14(2):154-172. http://dx.doi.org/10.1002/sys.20168.
85. Maslow A. H. A theory of human motivation. *Psychological Review*. 1943;50(4):370-396. http://dx.doi.org/10.1037/h0054346.
86. Mashlow AH. *Motivation and Personality*. New York: Harper and Row; 1954.
87. Max-Neef MA. *Human Scale Development: conception, application, and future reflections*. New York: Apex Press; 1991.
88. Max-Neef MA. Development and human needs. Ekins P, Max-Neef M. *Real-life economics*. London: Routledge; 1992.
89. Ullah A. M. M. Sharif, Sato Michihiro, Watanabe Michiko, Rashid Md. Mamunur. Integrating CAD, TRIZ, and Customer Needs. *International Journal of Automation Technology*. 2016;10(2):132-143. http://dx.doi.org/10.20965/ijat.2016.p0132.
90. Shafirovich E. Ya, Goldshleger U. I. Combustion of Magnesium Particles in CO2/CO Mixtures. *Combustion Science and Technology*. 1992;84(1):33-43. http://dx.doi.org/10.1080/00102209208951843.
91. Radanliev Petar, De Roure David C, Nurse Jason R. C, Mantilla Montalvo Rafael, Cannady Stacy, Santos Omar, Maddox La'Treall, Burnap Peter, Maple Carsten. Future developments in standardisation of cyber risk in the Internet of Things (IoT). *SN Applied Sciences*. 2020;2(2):http://dx.doi.org/10.1007/s42452-019-1931-0.
92. Rauch Erwin, Linder Christian, Dallasega Patrick. Anthropocentric perspective of production before and within Industry 4.0. *Computers & Industrial Engineering*. 2020;139:105644. http://dx.doi.org/10.1016/j.cie.2019.01.018.
93. Kaasinen Eija, Schmalfuß Franziska, Özturk Cemalettin, Aromaa Susanna, Boubekeur Menouer, Heilala Juhani, Heikkilä Päivi, Kuula Timo, Liinasuo Marja, Mach Sebastian, Mehta Rakesh, Petäjä Esko, Walter Thomas. Empowering and engaging industrial workers with Operator 4.0 solutions. *Computers & Industrial Engineering*. 2020;139:105678. http://dx.doi.org/10.1016/j.cie.2019.01.052.
94. Mourtzis D, Vlachou E, Dimitrakopoulos G, Zogopoulos V. Cyber- Physical Systems and Education 4.0 –The Teaching Factory 4.0 Concept. *Procedia Manufacturing*. 2018;23:129-134. http://dx.doi.org/10.1016/j.promfg.2018.04.005.
95. Aziz Hussin Anealka. Education 4.0 Made Simple: Ideas For Teaching. *International Journal of Education and Literacy Studies*. 2018;6(3):92. http://dx.doi.org/10.7575/aiac.ijels.v.6n.3p.92.

How to cite this article: Ullah AS. What is knowledge in Industry 4.0?. *Engineering Reports*. 2020;2:e12217. https://doi.org/10.1002/eng2.12217