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Collaborative knowledge management to identify data analytics opportunities in additive manufacturing

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Abstract
Additive Manufacturing (AM) is becoming data-intensive. The ability to identify Data Analytics (DA) opportunities for effective use of AM data becomes a critical factor in the success of AM. To successfully identify high-potential DA opportunities in AM requires a set of distinctive interdisciplinary knowledge. This paper proposes a methodology that enables collaborative knowledge management for identifying and prioritizing DA opportunities in AM. The framework of the proposed methodology has three components: a team of experts, a DA Opportunity Knowledge Base (DOKB), and a prioritization tool. The team of experts provides diverse knowledge that can be used to identify and prioritize DA opportunities. The DOKB, developed by using the Web Ontology Language (OWL), captures diverse knowledge from the experts to identify DA opportunities. The prioritization tool ranks the identified DA opportunities by using the Fuzzy integrated Technique of Order Preference Similarity to the Ideal Solution (Fuzzy-TOPSIS). A case study, in which National Institute of Standards and Technology (NIST) researchers participated, demonstrates our methodology. As a result, 264 DA opportunities for AM's Laser-Powder Bed Fusion (L-PBF) process are identified and prioritized. The prioritized DA opportunities help set a DA direction for L-PBF AM. Our methodology keeps knowledge sharable, reusable, revisable, and extendable. Thus, this methodology can continue to facilitate collaboration within the AM community to identify high potential and high impact DA opportunities in AM.

Keywords Additive manufacturing · Big data · Data analytics · Data-driven decision support · Knowledge-based system · Multiple criteria decision-making

Introduction

Additive manufacturing (AM) is an emerging manufacturing paradigm in which materials are joined layer-upon-layer to produce three-dimensional (3D) parts based on the 3D solid models (ASTM International, 2012). The layer-upon-layer characteristic of AM provides unique capabilities to achieve shape complexity, material complexity, hierarchical complexity, and functional complexity (Gibson et al., 2015). The capabilities of AM are expected to provide the manufacturing industry with numerous benefits, such as new

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opportunities for customization, an increased range of part geometries, and reduced manufacturing costs (Gibson et al., 2015).

To be practical and profitable, AM should achieve industrial competitiveness in quality, cost, and delivery (Eyers & Potter, 2017). Industrial competitiveness is affected by decision-making throughout the AM lifecycle including design process planning, building, post-processing, testing, and validation. For example, decision-making in process planning, such as setting scan speed, laser power, and scan strategy, affects not only the mechanical performance of the final part (Zhou et al., 2019), but also the cost of powder usage and build time (Bosio et al., 2019). However, making successful decisions is often limited by a lack of understanding of process-structure–property relationships in AM (Yuan et al., 2020). Until now, most of the decision-making techniques still rely on *ad-hoc* rules and engineering experience in AM (Mycroft et al., 2020). Thus, recent AM studies have been trying to improve decisions by using a knowledge-based approach (Mbow et al., 2021) or a data-driven approach (C. Wang et al., 2020). Especially, Data Analytics (DA) for decision-making has been attracting attention as a data-driven approach to reveal hidden patterns, correlations, and insights beyond the existing knowledge (C. Wang et al., 2020).

DA can be defined as a process of examining data to extract and create valuable information for decision-making (Koohang & Nord, 2021). Technologies that support DA applications in AM are continuously improved and developed. For example, advanced sensor technologies enable the capture of AM big data that can serve as inputs to DA (L. Wang & Alexander, 2016). Advanced High-Performance Computing (HPC) technologies allow AM big data to be processed more efficiently (L. Wang & Alexander, 2016). DA techniques including Machine Learning (ML) are available to analyze AM big data (C. Wang et al., 2020). These advanced technologies provide opportunities to exploit DA to improve decision-making in AM. However, identifying high-potential DA opportunities to exploit these advancements remains a challenge.

The ability to identify and prioritize a set of DA opportunities in AM is a critical factor in optimizing AM processes. Identifying DA opportunities allows potential DA opportunities to be captured before undertaking DA projects. Prioritization can then determine a top set of important and feasible DA opportunities. Our previous study (Park et al., 2019) introduced the concept of DA opportunity and provided a general framework for identification and prioritization. A DA opportunity can be characterized by a set of five tiers: “Goal”, “Activity”, “Data Analytics”, “Data”, and “Data Source” (Park et al., 2019). However, each tier considers a distinct area of knowledge (e.g., business, AM, DA, data), so interdisciplinary knowledge is required to identify and prioritize DA opportunities. A single expert seldom possesses such interdisciplinary knowledge. According to a Forbes Insight survey (Gagnon et al., 2017), the main difficulties encountered when designing DA initiatives are (1) lack of coordination among experts from diverse backgrounds and (2) lack of consistent methods and processes. We extend our previous study (Park et al., 2019) to solve these difficulties and enhance sharing, reuse, revision, and extension of the DA-opportunity knowledge. Our methodology systematically facilitates collaboration among diverse experts, and manages their knowledge with formal methods to identify the top DA opportunities in AM.

The developed methodology takes the Collaborative Knowledge Management (CKM) approach, which enables management of diverse knowledge from different experts. The methodology incorporates three major components: a team of experts, a DA Opportunity Knowledge Base (DOKB), and a prioritization tool. The team of experts is established to provide diverse knowledge for identifying and evaluating DA opportunities. The DOKB is developed by using the Web Ontology Language (OWL) (“OWL Web Ontology Language Overview” 2004) to capture the diverse knowledge and support identifying DA opportunities. The prioritization tool extends Fuzzy integrated Technique of Order Preference Similarity to the Ideal Solution (Fuzzy-TOPSIS) (NĂdĂban et al., 2016) to prioritize the identified DA opportunities by considering collaborative evaluation. This paper introduces the proposed methodology. It also provides a case study that demonstrates the proposed methodology for a laser powder bed fusion (L-PBF) AM process.

The remainder of this paper is organized as follows. Section 2 reviews the backgrounds of data-driven AM, ontology-based CKM, and Fuzzy-TOPSIS. Section 3 presents a methodology that uses the CKM approach to identify and prioritize DA opportunities in AM. Section 4 provides a case study of L-PBF AM. Section 5 concludes the paper.

Background

Data-driven AM, ontology-based CKM, and Fuzzy-TOPSIS are the foundation of the proposed methodology. In this section, the backgrounds of these three topics are introduced.

Data-driven additive manufacturing

Because of constant advances in sensor (Feng et al., 2020) and data management technologies (Majeed et al., 2019), AM is becoming increasingly data-intensive. AM processes can generate up to 600 variables and 75 gigabytes of image data per second (Razvi et al., 2019), resulting in a terabyte or more of data per build (Razvi et al., 2019). This data is in a variety of types including numerical data (e.g., machine logs), 2D images (e.g., thermal, optical), 3D (e.g., CAD models, CT scans), audio (e.g., acoustic signals), videos (e.g., thermal, optical), etc. (Razvi et al., 2019). The AM data can be collected from all AM lifecycle stages such as design (e.g., material properties and design parameters), process planning (e.g., process parameters), building (e.g., process signatures), post-processing (e.g., part structure), and testing and validation (e.g., part property and product performance) (Park et al., 2019).

Analyzing AM lifecycle data can uncover hidden patterns, correlations, and insights that help guide informed decisions and reduce potential risks. Advanced DA, such as Artificial Intelligence (AI) and ML, can effectively use AM big data to produce actionable intelligence and new knowledge for decision-makers. Advanced DA has successfully been applied to derive the relationships between (1) process parameters and creep rates (Sanchez et al., 2021), (2) process parameters and surface roughness (Xia et al., 2021), and (3) part geometry and printability (Mycroft et al., 2020). It has also been used to monitor layer defects and melt pool conditions in real time by analyzing temperature data (Mahato et al., 2020), acoustic signals (Ye et al., 2018), optical images (Davtalab et al., 2020; Kwon et al., 2020), and video-imaging data (Bugatti & Colosimo, 2021). AM activities such as process-parameter setting and in-situ monitoring were studied recently through applying advanced DA (C. Wang et al., 2020). To get maximum benefits from DA's capabilities, high-potential DA opportunities should be identified across the AM lifecycle.

Ontology-based collaborative knowledge management

CKM enables users from diverse backgrounds to achieve common goals by jointly creating, sharing, accessing, and applying knowledge across domain-specific or functional boundaries (Swarnkar et al., 2012). For example, Peng et al. (2017) designed and developed a CKM system to facilitate knowledge capture, retrieval, and reuse for users with different roles working on various tasks within the engineering design process. Other authors (Li et al., 2012; Wu & Gu, 2009) developed CKM systems to enable individuals in a series of organizations to collectively create, share, access, and apply knowledge across company boundaries to achieve the business objectives of the entire supply chain. Other examples include (1) the global company Aramex used CKM to manage its collective knowledge of disruptive technologies (v. Alberti-Alhtaybat et al., 2019); (2) Kamsu-Foguem and Noyes (2013) adopted CKM to compare and integrate different viewpoints of experts for industrial maintenance; (3) a CKM solution was implemented across the construction industry (Costa et al., 2013), which has a fragmented and ad-hoc nature; and, (4) the CKM approach was used in some biomedical communities (Dessì et al., 2016) where collaborative environments are required to share and create new knowledge.

An ontology is a formal, explicit specification of a representational vocabulary for a shared domain of discourse (Gruber, 1993) that can be used to enhance the usage of CKM. Ontologies are often used to share a common understanding of the knowledge and to enable the reuse of domain knowledge among people or software agents (Noy & McGuiness, 2001).In addition, an ontology enables automated reasoning to infer implicit knowledge and detect inconsistencies in a knowledge base (Keet, 2018).In AM applications, ontologies have been proposed (1) to promote the modeling and reuse of knowledge towards the assistance of design (Kim et al., 2019; Ko et al.,2021) and process planning (Liang, 2018) and (2) to be reused across computer systems to support knowledge and data management in an interoperable manner (Sanfilippo et al., 2019). Ontologies have been demonstrated as suitable to build a knowledge base for CKM (Abecker & van Elst, 2009). Adrian et al. (2014) presented a system for CKM, in which an ontology was used as a knowledge base to store, extract, and process knowledge about threats in an urban environment.

OWL ("OWL Web Ontology Language Overview" 2004) is a family of knowledge representation languages for authoring ontologies (Maniraj & Sivakumar, 2010). An ontology that uses OWL consists of classes, properties, and individuals. A class defines a group of individuals that belong together when they share certain properties ("OWL Web Ontology Language Overview" 2004). Properties include two types: an object property that represents the relationship between two individuals, and a data property that represents the relationship from some individual to a certain data value ("OWL Web Ontology Language Overview" 2004). Individuals are instances of classes. Property may be used to relate one individual to another ("OWL Web Ontology Language Overview" 2004). Semantic Web Rule Language (SWRL), also a knowledge representation language, extends OWL both syntactically and semantically by combining OWL with a Rule Markup Language (Horrocks et al., 2005). SWRL provides the ability to define complex rules and perform advanced reasoning on the concepts in an ontology (Ameri et al., 2012). Automated reasoning increases both the efficiency of processing the accumulated knowledge and the consistency of the inferred results. SWRL is in the form of an implication between an antecedent (body) and consequent (head) (Horrocks et al., 2004). Both antecedent and consequent are conjunctions of predicates, and variables are presented using the standard convention of prefixing them with a question mark.

Fuzzy-TOPSIS

TOPSIS (Hwang & Yoon, 1981) is a multiple-criteria, decision-making (MCDM) method to prioritize a list of alternatives. TOPSIS extends the concept that the chosen alternative should have two characteristics. First, it has the shortest distance to the Positive Ideal Solution (PIS), which minimizes the cost criteria and maximizes the benefit criteria. Second, it has the farthest distance from the Negative Ideal Solution (NIS), which maximizes the cost criteria and minimizes the benefit criteria. TOPSIS has four advantages over other MCDM methods (Lima Junior et al., 2014). It is: (1) able to produce a consistent preference order when a new alternative or criterion is introduced, (2) able to perform decision processes efficiently, (3) capable of prioritizing numerous alternatives, and (4) applicable to group decision-making. TOPSIS has proven its advantages when applied to prioritization in different areas such as mutual funds (Chang et al., 2010), suppliers (Sharma & Balan, 2013), intellectual capital indicators (Sekhar et al., 2015), and manufacturing equipment (P. Wang et al., 2017). However, TOPSIS and other MCDM methods all have a limited ability to capture vague information in an uncertain environment (Sirisawat & Kiatcharoenpol, 2018).

Fuzzy set theory (Zadeh, 1965) has been widely used to support decision-making when an evaluation or a judgment is made under uncertainty or with imprecise information. TOPSIS is therefore often integrated with the fuzzy set theory; such an integrated method is called Fuzzy-TOPSIS. Fuzzy-TOPSIS effectively prioritizes under fuzzy situations such as infrastructure projects (Liu & Wei, 2018), reverse-logistic solutions (Sirisawat & Kiatcharoenpol, 2018), sustainable-energy planning strategy (Solangi et al., 2019), and business models (Im & Cho, 2013). Because DA opportunities in AM are intangible, unmeasurable, uncertain, or imprecise, and thus difficult to evaluate, Fuzzy-TOPSIS is a good candidate to prioritize them.

Methodology

The methodology uses the CKM approach to identify and prioritize DA opportunities in AM. Figure 1 presents a framework of the proposed methodology. The framework consists of three major components: a team of experts, a

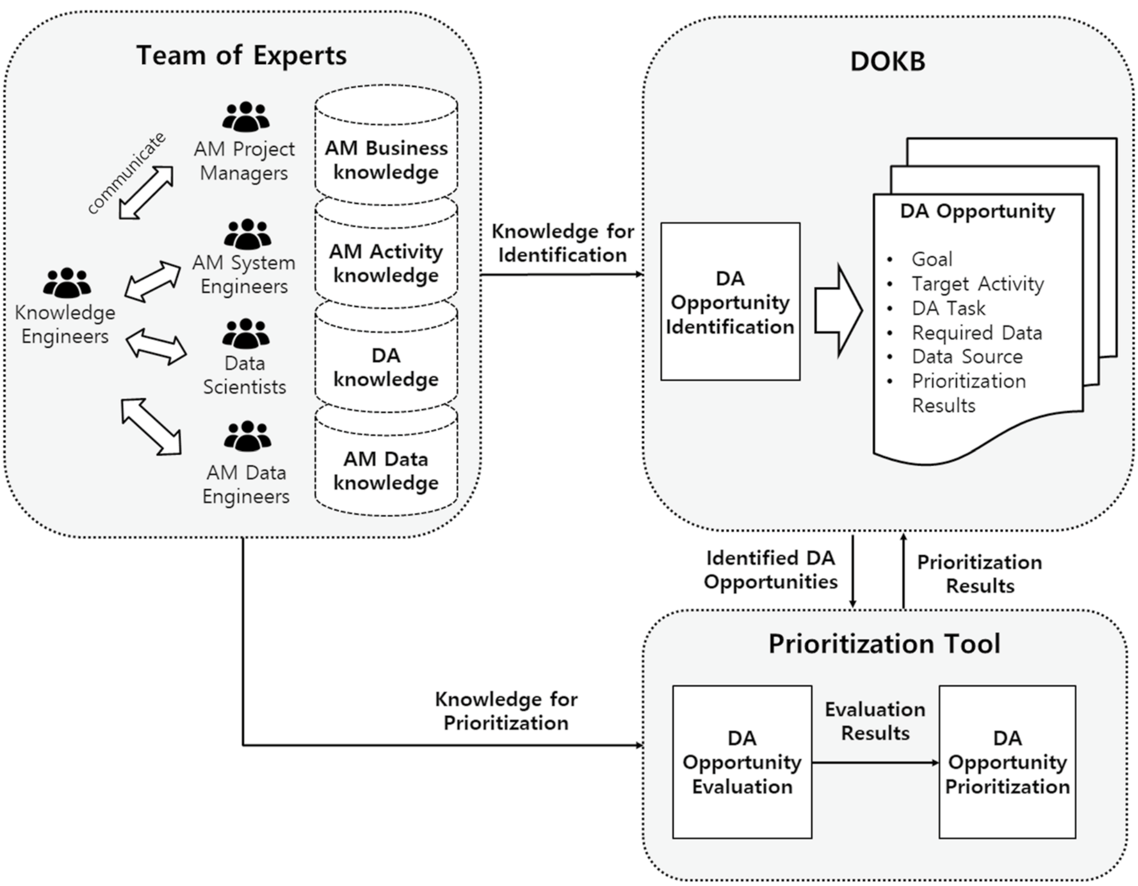

Fig. 1 A framework of the methodology to identify and prioritize DA opportunities in AM

DOKB, and a prioritization tool. The team of experts, preferably including AM project manager(s), AM system engineer(s), data scientist(s), AM data engineer(s), and knowledge engineer(s), provides diverse knowledge for identifying and prioritizing DA opportunities. The knowledge engineers lead both identification and prioritization tasks by communicating with the other experts. The DOKB captures the diverse knowledge from the team of experts by using OWL. This knowledge base supports the identification of DA opportunities. The prioritization tool prioritizes the identified DA opportunities by using the Fuzzy-TOPSIS. The prioritization results are also captured in the DOKB.

Team of experts

The team preferably includes five different groups of experts. Qualifications of each group are described as follows.

- AM project managers: knowledgeable about business requirements of AM to determine ultimate AM goals.
- AM system engineers: (1) knowledgeable about AM lifecycle and AM activities, (2) capable of identifying the AM activities for the target goals, and (3) capable of defining AM activities with input, control, output, and mechanism.
- Data scientists: (1) capable of defining DA tasks, (2) knowledgeable about DA techniques, and (3) capable of defining required data for each DA task.
- AM data engineers: (1) capable of preparing and managing AM data for the DA tasks, (2) capable of matching the required AM data to the AM data sources, and (3) knowledgeable about data acquisition.
- Knowledge engineers: (1) capable of processing experts' knowledge into the DOKB and (2) capable of supporting evaluation tasks.

Data analytics opportunity knowledge base

The DOKB is described in this section with a focus on the structure of the DOKB and how the DA opportunities are identified using the DOKB.

Knowledge base structure

The requirements of a knowledge base are typically defined using Competency Questions (CQs) (Grüninger & Fox, 1995). A DA opportunity is an opportunity for DA to make significant or other impacts on decision-making. In this sense, some of the CQs for the knowledge base include:

- Which goal should DA achieve?
- Which activity can DA make an impact?
- Which task can DA support for decision-making?
- Which data should DA perform?
- Which data source is required to collect the required data for DA?
- Which DA opportunity has the most significant impact considering importance and feasibility?

Considering these CQs, the DOKB uses the five-tier approach (Sect. 1; Park et al., 2019) to develop its structure. The five tiers are "Goal Tier", "Activity Tier", "Data Analytics Tier", "Data Tier", and "Data Source Tier". In the "Goal Tier", the goals in the target domain are defined. In the "Activity Tier", the activities that require decisions to meet individual target goals are defined. In the "Data Analytics Tier", the potential DA tasks that can help make those decisions are defined. In the "Data Tier", the required data for individual DA tasks are defined. In the "Data-Source Tier", the various sources that generate the required data are defined. As shown in Fig. 2, the DOKB's structure contains six major classes: "DataAnalyticsOpportunity", and one for each of the five tiers: "ThingDefinedintheGoalTier", "ThingDefinedintheActivityTier", "ThingDefinedintheDataAnalyticsTier", "ThingDefinedintheDataTier", and "ThingDefinedintheDataSourceTier". The last five major classes have sub-classes, as shown in Fig. 2. The subclasses denoted as "…" in Fig. 2 are additional classes required to enrich each tier's information after DA implementation but not essential in the identification process, so the additional classes are beyond the scope of this paper.

The "ThingDefinedintheGoalTier" class has a subclass "Goal" to define the goals to be achieved. The "Goal" class has three subclasses, "Quality", "Cost", and "Delivery", which are traditional strategic goals used by the manufacturing industry (Leong et al., 1990) including the AM industry (Eyers & Potter, 2017). The "Quality" class includes the target goals for the manufacture of product(s) that have high quality standards (Leong et al., 1990). The "Cost" class includes the target goals for production and distribution of the product(s) at a desired or predefined cost (Leong et al., 1990). The "Delivery" class includes the target goals to satisfy demand at the expedited time or the accurate process (Leong et al., 1990).

The "ThingDefinedintheActivityTier" class has three subclasses, "Activity", "ICOM", and "PerformanceIndicator", to define the activities that could achieve target goals. The concepts of classes "Activity" and "ICOM" are obtained from the IDEF0 method (National Institute of Standards & Technology, 1993), which is a standardized activity modeling method. The "Activity" class is used to describe AM activities. "Generate AM Design", "Plan Process", "Build Part", "Post Process Part", and "Test Part" are examples of AM lifecycle activities. These activities can be decomposed into sub-activities. For example, "Build Part" is decomposed into "Create Powder Layer", "Fuse Powders", and "Monitor

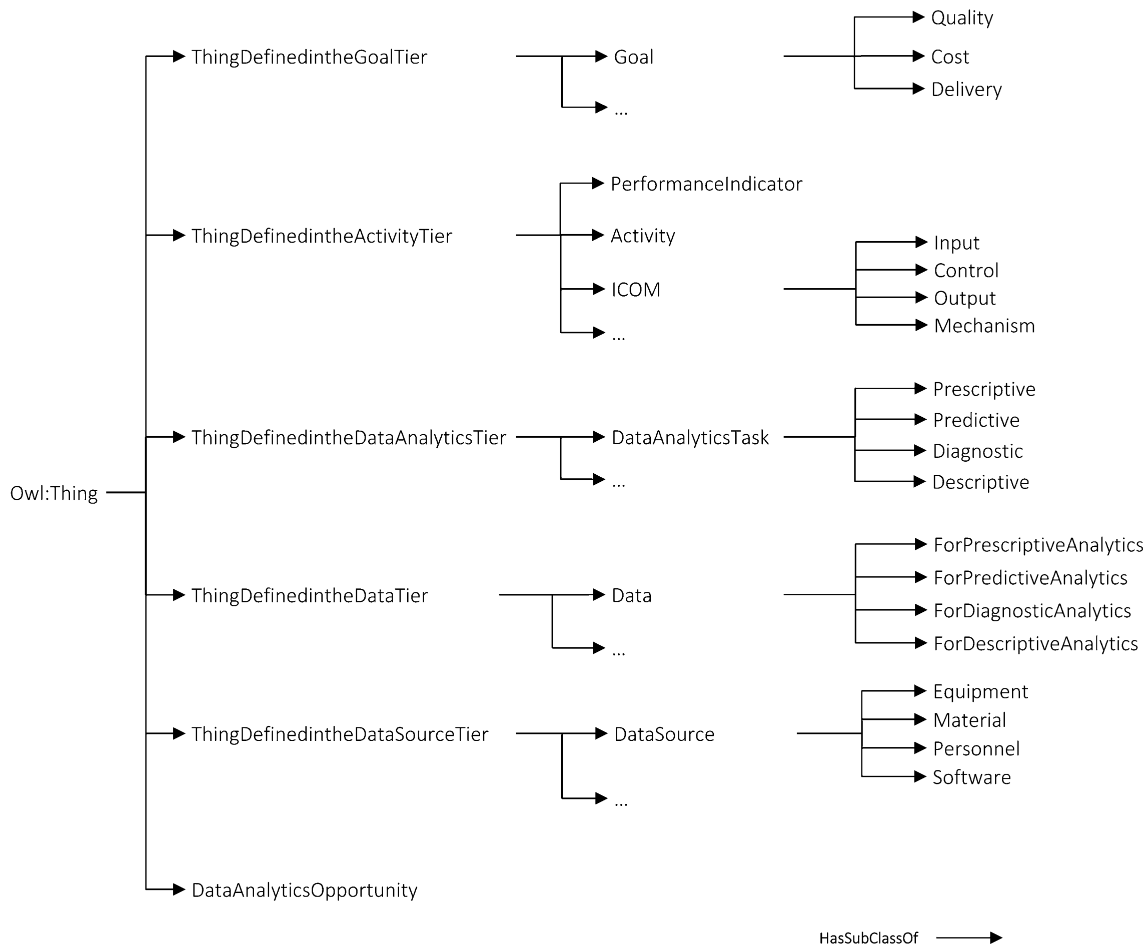

Fig. 2 The structure of the DOKB

Fusion". In IDEF0, inputs, controls, outputs, and mechanisms are collectively called ICOM. The "ICOM" class is used to define the concept of the activity; it consists of four subclasses: "Input", "Control", "Output", and "Mechanism". The "Input" class includes a set of objects that are transformed by the activity to produce outputs. The "Control" class includes a set of conditions that must be met to ensure that the activity produces the correct output. The "Output" class includes a set of results that are produced by the activity. The "Mechanism" class includes the means that support the execution of the activity. The "PerformanceIndicator" class includes a set of quantitative indicators that are measured in certain activities to evaluate the target goal.

The "ThingDefinedintheDataAnalyticsTier" class has a subclass "DataAnalyticsTask" to define DA tasks that potentially support decisions required in certain activities. The "DataAnalyticsTask" class has four subclasses: "Descriptive", "Diagnostic", "Predictive", and "Prescriptive" (Sallam et al., 2014). The "Descriptive" class includes DA tasks that characterize context from data; these tasks help decision-makers understand how their business or activity is performing. The "Diagnostic" class includes DA tasks that determine why their business or activity is performing as it is; those tasks use data mining techniques or other statistical analysis. The "Predictive" class includes DA tasks that predict unknown states or futures; those tasks use predictive ML techniques. The "Prescriptive" class includes DA tasks that prescribe various courses of actions or controls to maximize the goal. Those tasks use reinforcement learning, optimization techniques, or simulation.

The "ThingDefinedintheDataTier" class has a subclass "Data" to define required data for DA tasks. The required data is mapped to a specific DA task with one-to-one mapping. Hence, the "Data" class is classified into four subclasses that are based on the "DataAnalyticsTask" subclass types. The "ForPrescriptiveAnalytics" class includes data that have an objective variable, decision variables, and blocking variables. An objective variable is to be optimized, whereas decision variables are used to optimize the objective variable. The objective variable is affected by both decision variables and blocking variables, but blocking variables are not of interest to be prescribed. The

"ForPredictiveAnalytics" class includes data that have predictor variables and target variables. Predictor variables are used to predict, and target variables are variables to be predicted. The "ForDiagnosticAnalytics" class includes data that have explanatory variables and response variables. Explanatory variables are used to explain variations in responses, and response variables are variables to be explained. The "ForDescriptiveAnalytics" class includes data that are related to what DA should characterize. The classes in the DA and data tier are used to represent DA-specific knowledge with their properties. Table 11 and 12 (See Appendix.) show property examples of the classes.

The "ThingDefinedintheDataSourceTier" class has a subclass "DataSource" to define the origins of data; it is classified into four subclasses: "Equipment", "Software", "Personnel", and "Material", by reference to a classification of AM resources (Lu et al., 2015). The "Equipment" class includes AM-build equipment, post-processing equipment, and test equipment. The "Software" class includes CAD software, process optimization software, and build software. The "Personnel" class represents humans, such as designers, operators, and controllers, who have an active role in the AM lifecycle. The "Material" class includes raw material, semi-manufactures, and finished products.

The "DataAnalyticsOpportunity" class lists a collection of DA opportunities. To explicitly represent a DA opportunity, this class should answer the previously mentioned CQs. In this sense, each DA opportunity is defined as a set of a goal, a target activity, a DA task, required data, and required data sources; the information comes from "ThingDefinedintheGoalTier", "ThingDefinedintheActivityTier", "ThingDefinedintheDataAnalyticsTier", "ThingDefinedintheDataTier", and "ThingDefinedintheDataSourceTier". Figure 3 shows how "DataAnalyticsOpportunity" class is associated with the other classes. Also, the "DataAnalyticsOpportunity" class has data properties for storing the prioritization results, such as overall score, importance score,

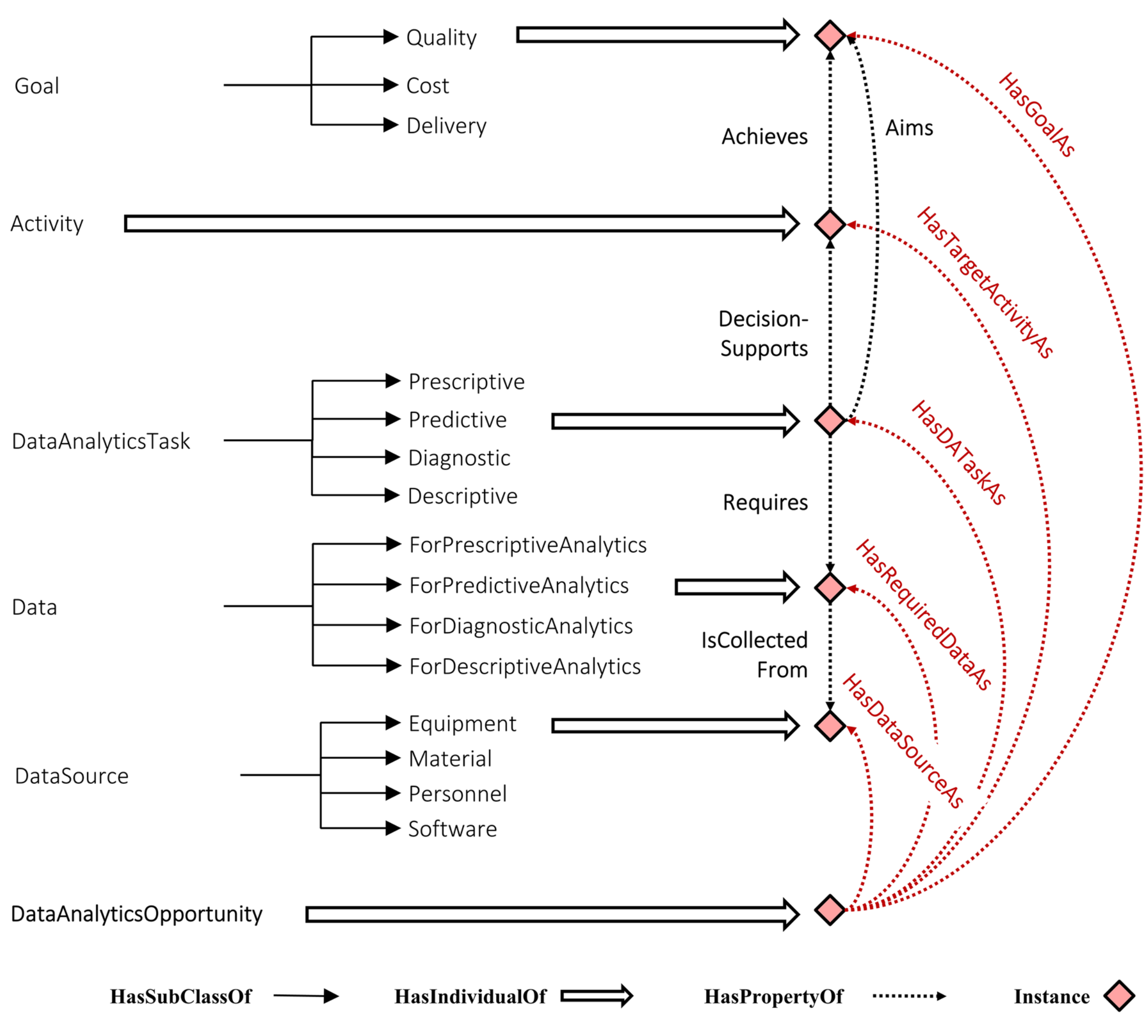

Fig. 3 The associations with the "DataAnalyticsOpportunity" class

and feasibility score. The prioritization results are generated by the prioritization tool, which is explained in Sect. 3.3.

Data analytics opportunity identification

The team of experts collaboratively identifies DA opportunities by defining instances of the classes in the DOKB. The DA opportunity identification process is shown in Fig. 4.

As described in Sect. 3.1, a team of experts may include five expert groups: AM project managers, AM system engineers, data scientists, AM data engineers, and knowledge engineers. Each group plays its unique role in supporting the identification of DA opportunities. Especially, knowledge engineers help each group to perform every knowledge-engineering task in this process.

The AM project managers define the "Goal" instances in "Quality", "Cost", or "Delivery" based on their business context. The AM system engineers define the activity-related instances, such as "Activity", "ICOM", and "PerformanceIndicator" instances, and the relationships among them based on the "Goal" instances and the scope of the target activity.

The data scientists define goal-oriented and AM activity-specific DA tasks by formulating and using SWRL rules. SWRL, (Sect. 2.2), allows an ontology reasoner, a software engine, to automatically identify properties of DA tasks in a consistent manner. SWRL rules should be formulated for "Prescriptive", "Predictive", "Diagnostic", and "Descriptive" individually by following the SWRL standard convention such as in the format of parent(?x,?y) ^ brother(?y,?z) uncle(?x,?z). For example, a predictive analytics rule can be formulated as.

IsEvaluatedBy(?*G*, ?*PI*) ^ IsMeasuredIn(?*PI*, ?*A*) ^ Predictive(?*DA*) ^ Aims(?*DA*, ?*G*) ^ Decision_Supports(?*DA*, ?*A*) ^ HasInputAs(?*A*, ?*I*) ^ HasControlAs(?*A*, ?*C*)—> Predicts(?*DA*, ?*PI*) ^ Considers(?*DA*, ?*I*) ^ Considers(?*DA*, ?*C*).

This rule indicates when a predictive analytics task is determined to support a certain activity and its goal, the task predicts a performance indicator that is measured in the activity to evaluate the goal by considering the information retrieved from the inputs and controls of the activity.

Similarly, the data scientists define required data for individual DA tasks using SWRL that include rules for "ForPrescriptiveAnalytics", "ForPredictiveAnalytics", "ForDiagnosticAnalytics", and "ForDescriptiveAnalytics". For example, a predictive analytics data requirement rule can be formulated as.

IsRequiredBy(?*D*, ?*DA*) ^ Predictive(?*DA*) ^ Predicts(?*DA*, ?*Y*) ^ Considers(?*DA*, ?*X*)—> HasPredictorVariableAs(?*D*, ?*X*) ^ HasTargetVariableAs(?*D*, ?*Y*).

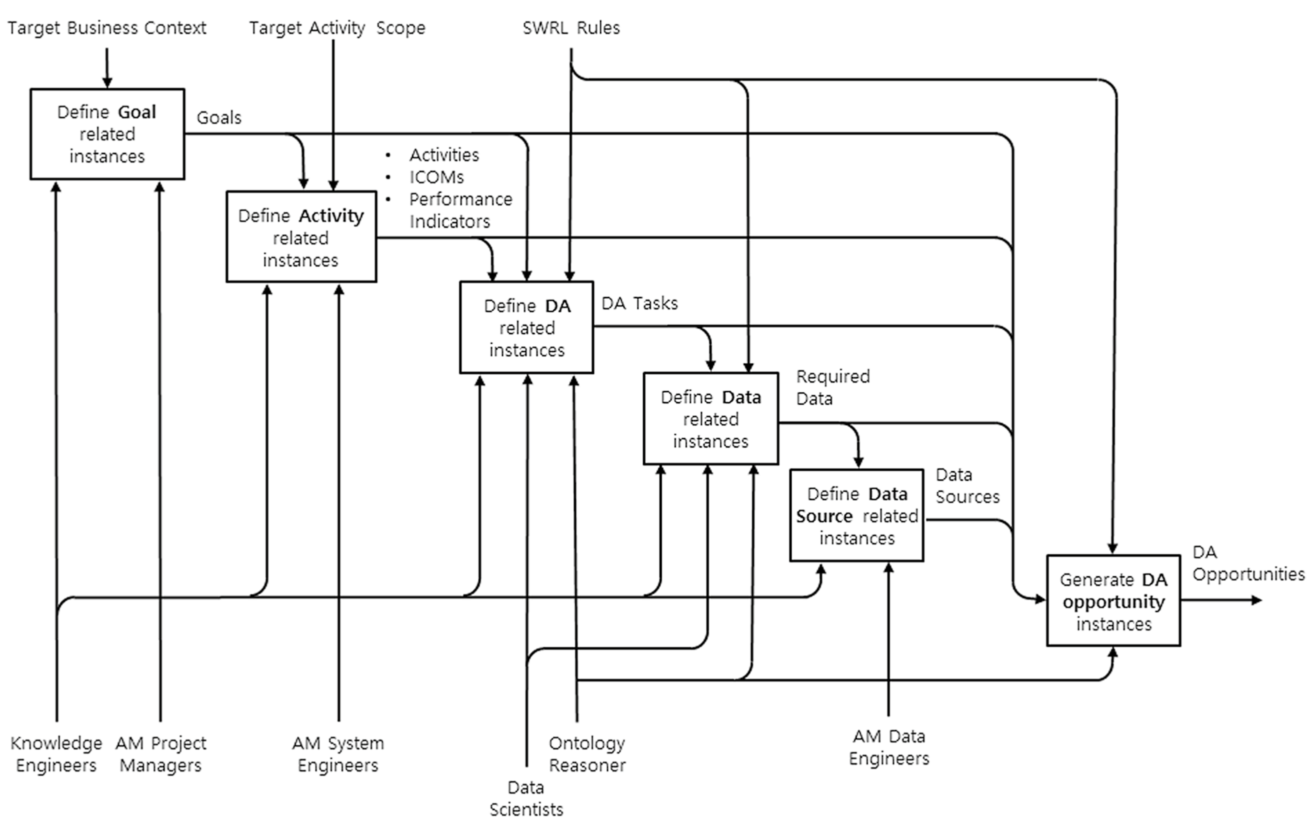

Fig. 4 DA opportunity identification process

This rule indicates when data are required by a certain predictive analytics task, the data should include the predictor variables for what information the task should consider and the target variables for what the task should predict.

The AM data engineers define the instances of "DataSource" from which the required data is collected. "DataSource" instances are established based on certain variables defined in the "Data" instance. For example, when a "Data" instance includes a variable of deviation of melt pool dimension, its "DataSource" instance may be a coaxial camera.

Finally, "DataAnalyticsOpportunity" instances are generated by composing the instances defined above. Thus, a "DataAnalyticsOpportunity" instance is associated with each of its source instances, as shown in Fig. 3. An SWRL rule to generate "DataAnalyticsOpportunity" instances is formulated as.

HasDataAnalyticsTaskAs(?*DO*, ?*DA*) ^ Decision_Supports(?*DA*, ?*A*) ^ Aims(?*DA*, ?*G*) ^ Achieves(?*A*, ?*G*) ^ Requires(?*DA*, ?*D*) ^ IsCollectedFrom(?*D*, ?*DS*)—> HasGoalAs(?*DO*, ?*G*) ^ HasTargetActivityAs(?*DO*, ?*A*) ^ HasRequiredDataAs(?*DO*, ?*D*) ^ HasDataSourceAs(?*DO*, ?*DS*).

where *DO*, *G*, *A*, *DA*, *D*, and *DS* represent a "DataAnalyticsOpportunity" instance, "Goal" instance, "Activity" instance, "DataAnalyticsTask" instance, "Data" instance, and "DataSource" instance, respectively.

For example, a "DataAnalyticsOpportunity" instance *DO* has a *DA* task instance that predicts *Porosity*. The *DA* can support the *FusePowders* activity instance and aim at the *MechanicalPerformanceImprovement* goal instance. In the same example, *DA* requires a *D* data instance, which has predictor variables of *PowderLayer*, *QualityParameter*, *RecoatingParameter*, *ControlParameter*, and *PowderFusionParameter*; and a target variable of *Porosity*. *D* requires data sources as *ProcessPlanningSoftware*, *LayerwiseCamera* and *X-rayComputedTomographyScanner (XCT)*. Thus, the *DO* has *MechanicalPerformanceImprovement* as its goal, *FusePowders* as its target activity, *DA* as its DA task, *D* as the required data, *ProcessPlanningSoftware*, *LayerwiseCamera*, and *XCT* as the required data sources.

Prioritization tool

For the sake of time, cost, and impact, there is no need to realize all identified DA opportunities. The tool helps to identify high potential and high impact DA opportunities. The prioritization tool includes two phases: Evaluation and Prioritization. During the Evaluation phase, the team of experts evaluates each identified DA opportunity. The Prioritization phase focuses on prioritizing the DA opportunities by assessing the evaluation results from the team of experts using the Fuzzy-TOPSIS. After prioritization, each DA opportunity has an overall score, an importance score, and a feasibility score.

Data analytics opportunity evaluation

The team of experts evaluates the identified DA opportunities using the six criteria in Table 1. Each DA opportunity consists of the five-tier information, so each criterion is to evaluate one of the five tiers of each DA opportunity. Benefit criteria C_1, C_2, and C_3 are related to goal, activity, and DA, respectively. Cost criteria C_4, C_5, and C_6 are related to DA, data, and data source, respectively.

Each DA opportunity is evaluated based on the six criteria using seven linguistic variables: Very High (VH), High (H), Slightly High (SH), Medium (M), Low (L), Slightly Low (SL), and Very Low (VL). For example, an expert evaluates DA opportunity DO_1 and DO_2. DO_1 has a goal *MechanicalPerformanceImprovement,* and DO_2 has a goal *MaterialSaving*. If the expert thinks the benefit of achieving *MechanicalPerformanceImprovement* is very high and achieving *MaterialSaving* is high; the expert can rate DO_1 and DO_2 as VH and H on C_1.

Each expert also self-evaluates his/her level of expertise on each criterion by using the same variables. For example, project managers may rate their expertise as VH on C_1 but not on the other criteria.

Data analytics opportunity prioritization

The evaluated DA opportunities are prioritized using Fuzzy-TOPSIS. Fuzzy sets allow for a concept called 'partial truth',

Table 1 Criteria for evaluating DA opportunities

Criterion	Description
C_1	Benefit for achieving the goal
C_2	Benefit for improving the activity to achieve the corresponding goal
C_3	Benefit for performing the DA task to support making decisions to the corresponding activity
C_4	Difficulty of performing the DA task assuming the required data is available
C_5	Difficulty of managing the required data to be prepared for the DA task
C_6	Difficulty of collecting the required data from the data sources

where the truth-value ranges between 0 and 1. The fuzzy sets model uncertainty in judgment; this contrasts with binary sets, which have two, deterministic elements (true and false). Quantifying the concept of partial truth involves creating a fuzzy set $\tilde{x}$ in which elements are defined by a membership function $\mu_{\tilde{x}}(t)$, which assigns each element t a membership degree in the interval [0, 1]. A Triangular Fuzzy Number (TFN) is a fuzzy set denoted as $\tilde{x} = \left(x_1, x_2, x_3\right)$, where x_1, x_2, and x_3 are the lower limit, the value with the largest membership function value, and the upper limit, respectively. The membership function associated with a TFN is defined in Eq. (1).

$$\mu_{\tilde{x}}(t) = \begin{cases} \left(t - x_1\right)/\left(x_2 - x_1\right), & x_1 \le t \le x_2 \\ \left(x_3 - t\right)/\left(x_3 - x_2\right), & x_2 \le t \le x_3 \\ 0, & otherwise \end{cases} \tag{1}$$

A linguistic variable can be expressed as a TFN to describe the subjective judgment quantitatively, as shown in Table 2.

Algebraic operations with TFNs are described as Eq. (2)–(6).

Let $\tilde{a} = \left(a_1, a_2, a_3\right)$ and $\tilde{b} = \left(b_1, b_2, b_3\right)$ be two TFNs.

$$\tilde{a} \pm \tilde{b} = \left(a_1 \pm b_1, a_2 \pm b_2, a_3 \pm b_3\right) \tag{2}$$

$$\tilde{a} \times \tilde{b} = \left(a_1 \times b_1, a_2 \times b_2, a_3 \times b_3\right) \tag{3}$$

$$\tilde{a} \div \tilde{b} = \left(a_1 \div b_1, a_2 \div b_2, a_3 \div b_3\right) \tag{4}$$

$$r \times \tilde{a} = \left(r \times a_1, r \times a_2, r \times a_3\right) \tag{5}$$

where r is a constant number

$$\mathrm{d}(\tilde{a}, \tilde{b}) = \sqrt{\left\{\left(a_1 - b_1\right)^2 + \left(a_2 - b_2\right)^2 + \left(a_3 - b_3\right)^2\right\}/3} \tag{6}$$

where $\mathrm{d}(\tilde{a}, \tilde{b})$ is the distance between $\tilde{a}$ and $\tilde{b}$.

Collaborative evaluation based on the Fuzzy-TOPSIS method encounters a drawback: the knowledge levels of all evaluators are treated the same. We modified the existing Fuzzy-TOPSIS to consider the expertise level of each expert on each criterion. The process procedure of the modified Fuzzy-TOPSIS is described as follows:

Step 1 Assign a TFN to each linguistic variable.

The linguistic variables are quantified as the corresponding TFNs in Table 2. The fuzzy rating of the k^{th} expert about the i^{th} DA opportunity DO_i with respect to the j^{th} criterion C_j is denoted $\tilde{x}_{ij}^k = \left(x_{ij1}^k,\ x_{ij2}^k,\ x_{ij3}^k\right)$. The expertise level of the k^{th} expert on criterion C_j is denoted $\tilde{w}_j^k = \left(w_{j1}^k,\ w_{j2}^k,\ w_{j3}^k\right)$.

Step 2 Compute weighted aggregated fuzzy ratings for the DA opportunities.

The aggregated fuzzy rating of DO_i with respect to C_j is computed using Eq. (7):

$\tilde{x}_{ij} = \left(x_{ij1}, x_{ij2}, x_{ij3}\right)$,where

$$x_{ij1} = \sum_{k=1}^{K} x_{ij1}^k \times w_{j1}^k,\ x_{ij2} = \sum_{k=1}^{K} x_{ij2}^k \times w_{j2}^k,\ x_{ij3} = \sum_{k=1}^{K} x_{ij3}^k \times w_{j3}^k \tag{7}$$

After this above operation, the aggregated fuzzy rating reflects the expertise level of each individual expert.

Step 3 Compute the normalized fuzzy decision matrix.

Let the criteria (C_1,…,C_m) be the benefit criteria and the criteria (C_{m+1},…,C_n) be the cost criteria. The normalized fuzzy decision matrix is represented by Eq. (8).

$\tilde{R}$= [$\tilde{r}_{ij}$],where

$$\tilde{r}_{ij} = \left(x_{ij1}/x_j^*,\ x_{ij2}/x_j^*,\ x_{ij3}/x_j^*\right)\ and\ x_j^* = \max_i\{x_{ij3}\},\quad j = 1, \dots, m$$
$$or$$
$$\tilde{r}_{ij} = \left(x_j^-/x_{ij3},\ x_j^-/x_{ij2},\ x_j^-/x_{ij1}\right)\ and\ x_j^- = \min_i\{x_{ij1}\},\quad j = m+1, \dots, n \tag{8}$$

Step 4: Compute the Fuzzy Positive Ideal Solution (FPIS) and Fuzzy Negative Ideal Solution (FNIS).

The FPIS and FNIS are calculated as Eq. (9) and (10):

$$\text{FPIS} = \left(\tilde{r}_1^*, \tilde{r}_2^*, \dots, \tilde{r}_n^*\right),\ \text{where}\ \tilde{r}_j^* = \max_i\{r_{ij3}\} \tag{9}$$

$$\text{FNIS} = \left(\tilde{r}_1^-, \tilde{r}_2^-, \dots, \tilde{r}_n^-\right),\ \text{where}\ \tilde{r}_j^- = \min_i\{r_{ij1}\} \tag{10}$$

Step 5: Compute the distances from each DA opportunity to the FPIS and to the FNIS.

In this step, the distances from each DA opportunity to the FPIS (d_{ij}^*) and to the FNIS (d_{ij}^-) on each criterion are computed as Eq. (11) and (12):

$$d_{ij}^* = d\left(\tilde{r}_{ij}, \tilde{r}_j^*\right) \tag{11}$$

$$d_{ij}^- = d\left(\tilde{r}_{ij}, \tilde{r}_j^-\right) \tag{12}$$

Table 2 Linguistic variables and corresponding TFNs

Linguistic variable	TFN
Very High (VH)	(6,7,7)
High (H)	(5,6,7)
Slightly High (SH)	(4,5,6)
Medium (M)	(3,4,5)
Slightly Low (SL)	(2,3,4)
Low (L)	(1,2,3)
Very Low (VL)	(1,1,2)

Step 6: Compute the closeness coefficients for each DA opportunity.

For each DO_i, the closeness coefficients can be calculated for two different dimensions— importance ICC_i and feasibility FCC_i—to represent importance score and feasibility score, respectively. OCC_i is also calculated as an overall score that considers both importance and feasibility. This score is meant to provide a single metric to determine overall high-impact DA opportunities.

ICC_i is calculated using the benefit criteria:

$$ICC_i = \sum_{j=1}^{m} d_{ij}^- / \sum_{j=1}^{m} (d_{ij}^* + d_{ij}^-) \tag{13}$$

FCC_i is calculated using the cost criteria:

$$FCC_i = \sum_{j=m+1}^{n} d_{ij}^- / \sum_{j=m+1}^{n} (d_{ij}^* + d_{ij}^-) \tag{14}$$

OCC_i is calculated using all criteria:

$$OCC_i = \sum_{j=1}^{n} d_{ij}^- / \sum_{j=1}^{n} (d_{ij}^* + d_{ij}^-) \tag{15}$$

Case Study

To demonstrate the feasibility of the proposed methodology, we provide a case study that shows how high potential and high impact DA opportunities are identified to support AM research at NIST. NIST's AM research goal is to help innovate and improve AM industrial competitiveness. To achieve this goal, NIST has developed the Additive Manufacturing Metrology Testbed (AMMT) to conduct advanced research on the L-PBF process (Lane et al., 2016). This study identifies and prioritizes DA opportunities in AMMT, specifically for the L-PBF process.

Team of Experts

NIST is a research institute where experts from various backgrounds gather. Currently, NIST runs two AM projects related to DA: Data-Driven Decision Support for Additive Manufacturing (3DSAM) (Witherell & Lee, 2020) and Data Integration and Management for Additive Manufacturing (DIMAM) (Lu & Jones, 2020). The objective of the 3DSAM project is to develop and deploy metrics, models, and best practices for using product definition, advanced analytics, and DA methods in AM design and process planning to achieve target AM goals (Witherell & Lee, 2020). The objective of the DIMAM project is to develop models, methods, and best practices for data lifecycle management, data integration, and data fusion in AM to facilitate the effective and efficient curation, sharing, processing, and use of AM data (Lu & Jones, 2020).

For this use case study, a six-expert team was formed from the two projects. This team satisfies the qualification requirements described in Sect. 3.1.

Identification of data analytics opportunities

A DOKB was developed using the Protégé tool, which is an open-source software program for ontology development. The structure of the DOKB in Protégé is presented in Fig. 5.

The expert team defined seven instances of the "Goal" class: for the L-PBF process, *Conformance, AestheticImprovement*, and *MechanicalPerformanceImprovement* are defined in "Quality"; *MaterialSaving* and *EnergySaving* are defined in "Cost"; and *TimeEfficiency* and *ProcessStability* are defined in "Delivery". To define activity-related instances, the experts adopted the existing IDEF0 model for the L-PBF process, which was previously developed by NIST researchers (Kim et al., 2017). A set of activities that can achieve the seven "Goal" instances was chosen from the IDEF0 model. As a result, 23 "PerformanceIndicator" instances, 19 "Activity" instances, and all activity-instance related "ICOM" instances were identified and associated. For example, the "PerformanceIndicator" instance *Porosity* and the "Activity" instance *FusePowders* were identified for the "Goal" instance *MechanicalPerformanceImprovement*. Figure 6 provides a visual representation of the example, including the relationships among the instances.

The team of experts defined goal-oriented and AM activity-specific DA tasks by formulating five SWRL rules, as shown in Table 13 (a) (See Appendix). Using the rules, 264 "DataAnalyticsTask" instances were automatically defined; they include 66 instances for each subclass—i.e., "Prescriptive", "Predictive", "Diagnostic", and "Descriptive". One instance example of DA_{106} is shown in Fig. 7 (a). The "Predictive" instance DA_{106} is for supporting the activity *FusePowders* and the goal *MechanicalPerformanceImprovement*. Six new properties (yellow box) of DA_{106} were inferred using the Predictive Analytics Rule. DA_{106} is for predicting *Porosity* using the information of *QualityParameter*, *RecoatingParameter*, *ControlParameter*, *PowderFusionParameter*, and *PowderLayer*. The expert team also defined required data for individual DA tasks by formulating four SWRL rules, as shown in Table 13 (b) (See Appendix). In total, 264 "Data" instances were defined for the "DataAnalyticsTask" instances, including 66 instances for each subclass—i.e., "ForPrescriptiveAnalytics", "ForPredictiveAnalytics", "ForDiagnosticAnalytics", and "ForDescriptiveAnalytics". One instance example of D_{106} is shown in Fig. 7(b). The "ForPredictiveAnalytics" instance, D_{106} is required by DA_{106}. Six new properties (yellow box) of D_{106} were inferred using the

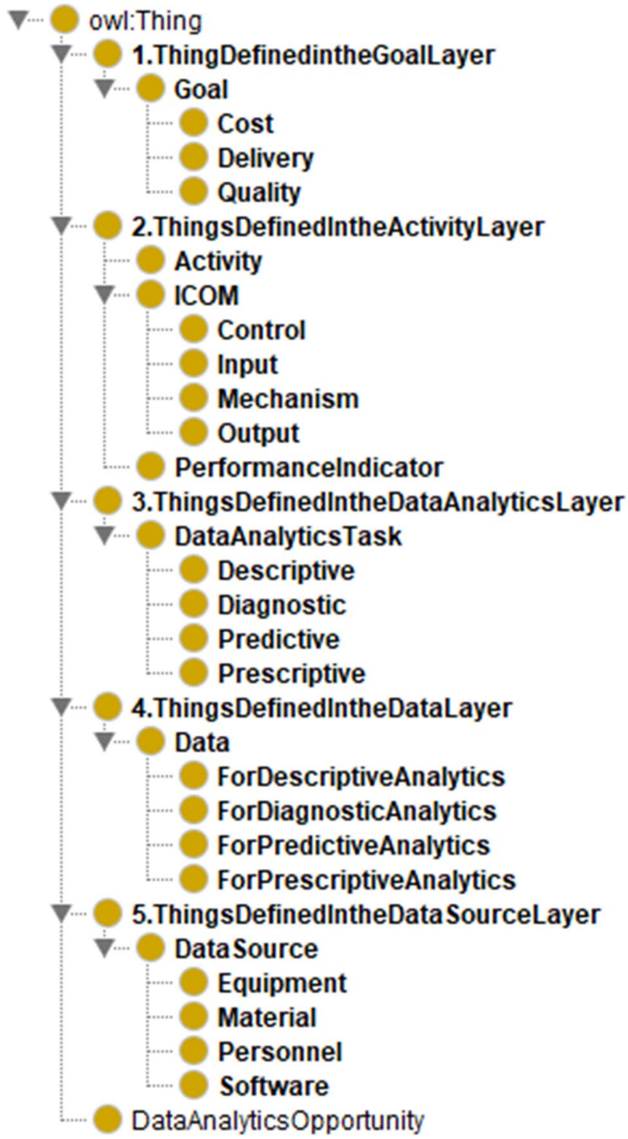

Fig. 5 Structure of DOKB in Protégé

Predictive Analytics Data Requirement Rule. D_{106} includes the predictor variables of *QualityParameter*, *RecoatingParameter*, *ControlParameter*, *PowderFusionParameter*, and *PowderLayer* and a target variable of *Porosity*.

The experts defined the instances of "DataSource" by referring to the variables of the required "Data" instances. In total, 26 "DataSource" instances were identified: 16 "Equipment" instances, three "Material" instances, one "Personnel" instance, and six "Software" instances. For example, D_{106} can be collected from *ProcessPlanningSoftware* in the "Software" class and from *LayerwiseCamera* and *XCT* in the "Equipment" class (Fig. 8).

Finally, 264 DA opportunities were identified for the L-PBF process (Fig. 9), with DO_{106} as one of the identified DA opportunities. DO_{106} was developed based on the goal *MechanicalPerformanceImprovement*; the target activity *FusePowders*; the DA task DA_{106}; required data D_{106}; and data sources *XCT*, *LayerwiseCamera*, and *ProcessingPlanningSoftware*. Additional information about each instance can be retrieved from the DOKB, as shown in Fig. 9. In addition, DO_{106} provides the prioritization results, which are described in the next sub-section.

Evaluation and prioritization of data analytics opportunities

The team of six experts ($E_1 - E_6$) evaluated the identified DA opportunities. Each expert has a unique knowledge background. Table 3 shows how much each expert knows about each criterion (described in Table 1) using the seven linguistic variables described in Table 2. Table 4 presents the results of the evaluation for each DA opportunity using these same linguistic variables.

The linguistic variables in Tables 3 and 4 were quantified to the corresponding TFNs (described in Table 2). For example, the expertise of E_1 on the criterion C_1 is SH, so the fuzzy rating of the expertise is denoted as (4,5,6). The linguistic rating of E_1 on DO_1 with respect to criterion C_1 is SH, so E_1's fuzzy rating is also denoted as (4,5,6). Then, the weighted, aggregated fuzzy rating was calculated using Eq. (7). Table 5 presents the weighted aggregated fuzzy matrix.

The normalized fuzzy decision matrix, $\tilde{R}=[\tilde{r}_{ij}]$, was computed using Eq. (8). Table 6 presents the normalized fuzzy decision matrix.

The FPIS and FNIS were calculated using Eq. (9) and (10). Table 7 presents the results of FPIS and FNIS for all criteria.

The distances from each DA opportunity to FPIS and to the FNIS were computed using Eq. (11) and (12) after FPIS and FNIS were determined. Finally, the closeness coefficients of DO_i were calculated for importance (ICC_i), feasibility (FCC_i), and overall (OCC_i) using Eq. (13–15). Table 8 presents examples of the distances and the closeness coefficients with priority rankings.

Analysis of prioritization results

The prioritization results of the identified DA opportunities can be further analyzed using a prioritization matrix. The feasibility dimension (x axis) and importance dimension (y axis) in the matrix represent the closeness coefficients FCC_i and ICC_i of DO_i, respectively. The value of OCC_i is used to determine the circle size of DO_i in the prioritization matrix. The prioritization results (see Table 8 for examples) were sorted into four groups, as shown in Table 9 and Fig. 10. By mapping DA opportunities to a prioritization matrix, we are able to present the user with graphical means

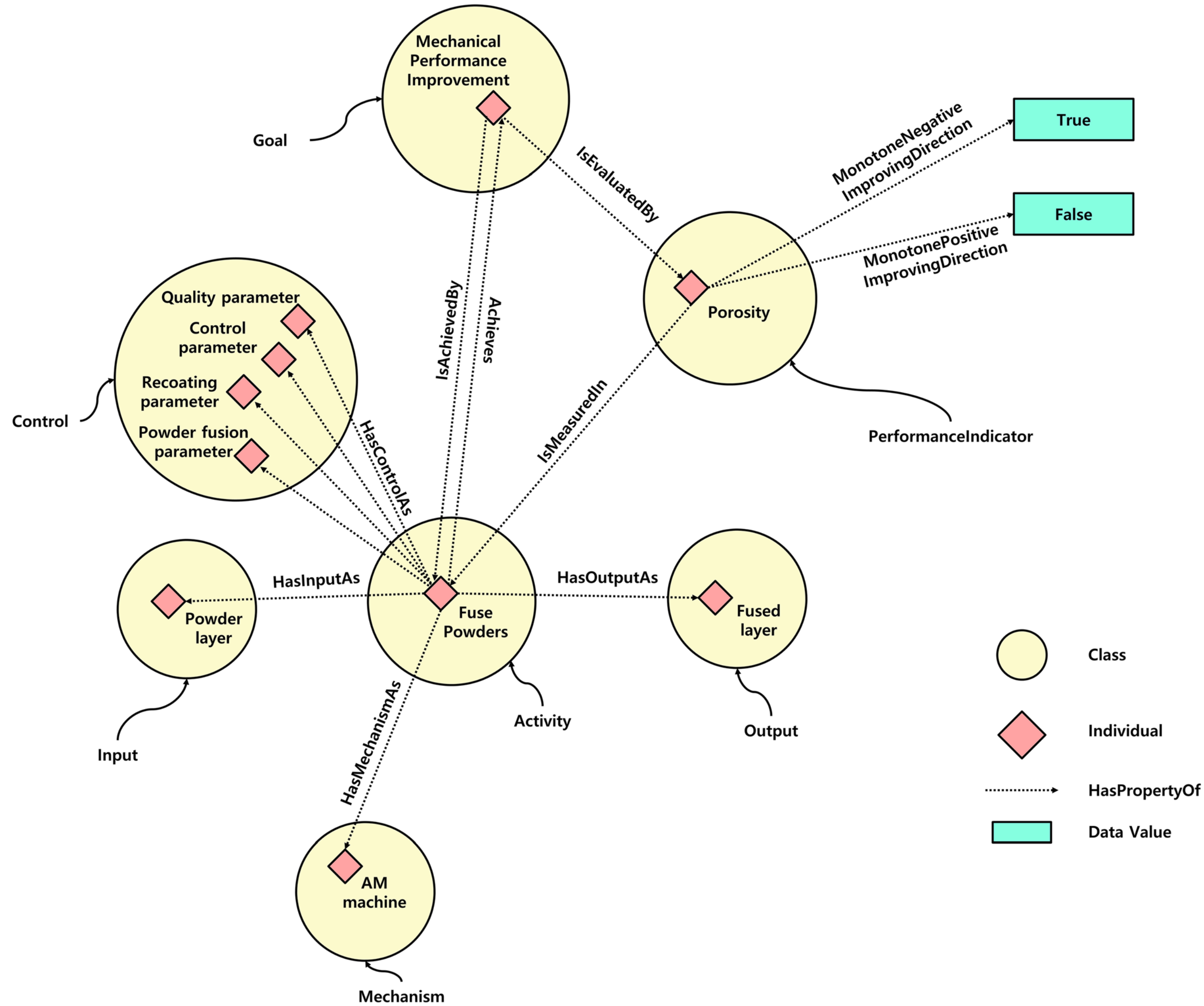

Fig. 6 An illustrative example of the established relationship for L-PBF in the DOKB

for interpreting the overall results. Location of the opportunities in the four quadrants correlates with the potential impact of DA opportunities. The first group G1 has critical DA opportunities. The second group G2 has DA opportunities that are potentially critical. A DA opportunity in G2 can be re-prioritized in G1 by making a special effort to improve the feasibility. The third group G3 has DA opportunities with the lowest priority. The fourth group G4 has DA opportunities that may be easy to develop, but most likely, the effort is not beneficial; however, sometimes, such opportunities might be helpful for proof of DA concept in emerging areas.

As shown in Table 10, the prioritization results of three DA-opportunity examples were tabulated to summarize the ICC, FCC, and OCC scores and ranks, as well as the five-tier information of each example opportunity. Considering OCC, DO_{136} ranked first among the 264 identified DA opportunities. It is therefore worth examining the opportunity DO_{136}. The task for DO_{136} is to characterize support structures to determine their number and size for the part overhangs. The goal of this opportunity is to reduce the amount of material used to build support structures, while the target activity is meant to design a support for overhangs. Many historical data of support structures on similar designs from process planning software are now available to realize this DA opportunity. Realizing this DA opportunity will improve understanding of how much waste material can be reduced.

DO_{106} and DO_{119} are two special opportunities because they have very high ICC scores and are ranked at the top; however, they are considered potentially critical opportunities (G2). The goal of these two opportunities is to improve mechanical performance, which is directly related to part

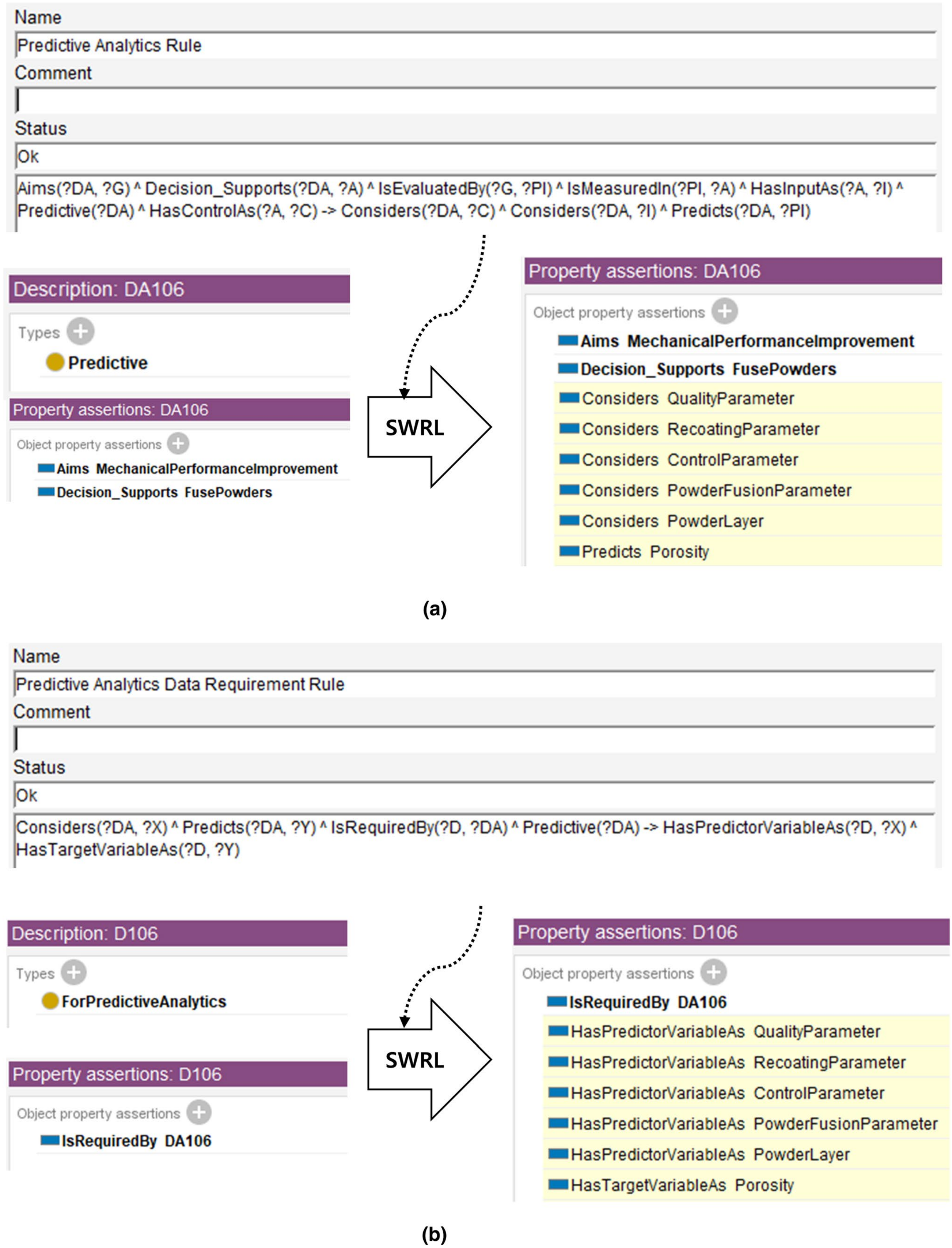

Fig. 7 Examples of newly inferred properties using SWRLs (**a**) for a “Predictive” instance, and (**b**) for a “ForPredictiveAnalytics” instance

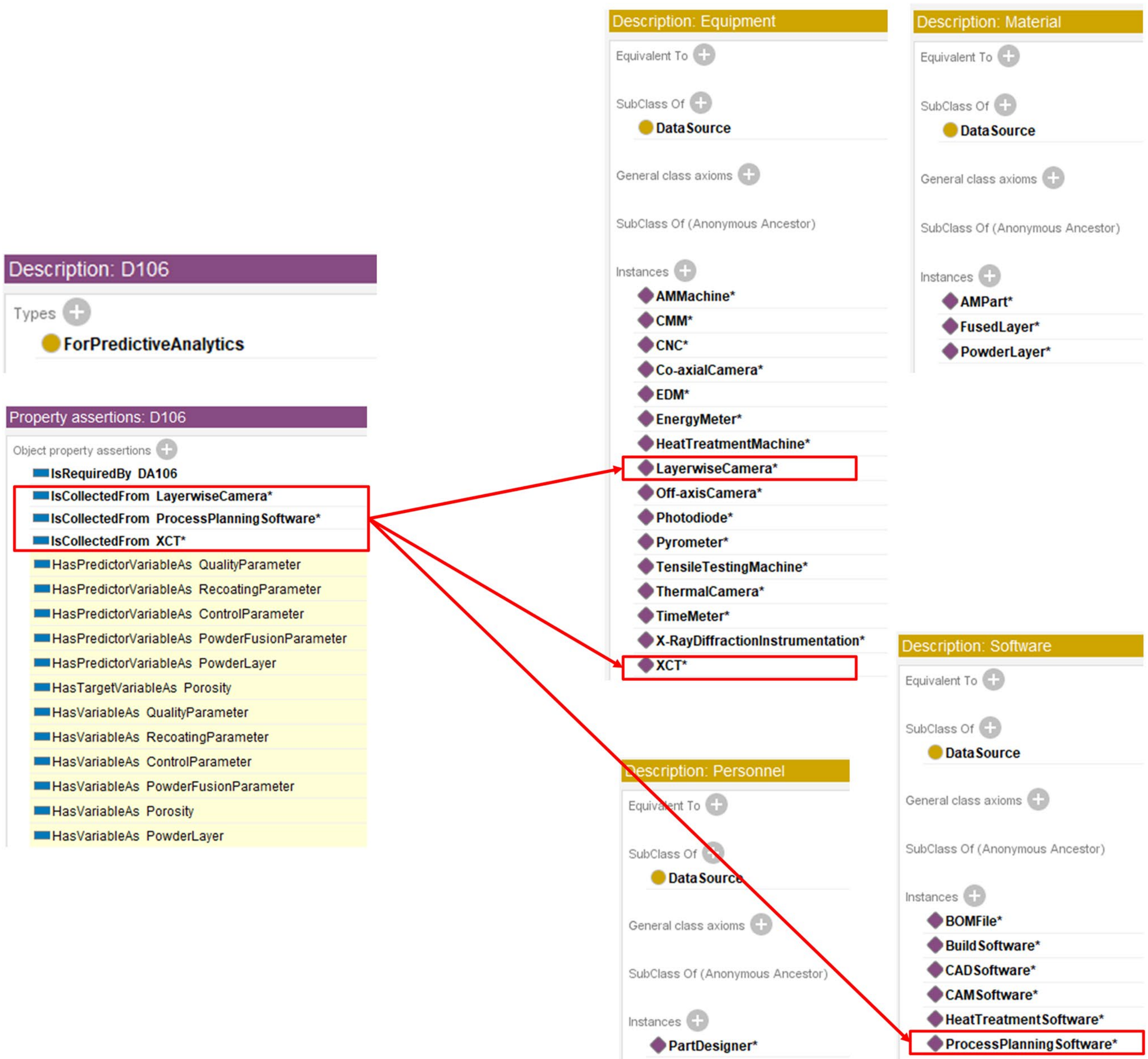

Fig. 8 An example of data sources for D_{106}

quality. Poor AM part quality is a major obstacle that hinders the widespread adoption of AM technology. DO_{106} predicts porosity by considering a powder layer and parameters for quality, control, powder fusion, and recoating. The prediction could improve real-time control when fusing powders and lead to AM products having higher mechanical performance. DO_{119} diagnoses residual stress by identifying a correlation between 1) residual stress and 2) AM part and heat treatment parameters. Newly identified data-driven knowledge, if provided, could help set heat treatment parameters to improve properties of AM parts. Despite their very high ICC scores, DO_{106} and DO_{119} receive very low FCC scores (0.057 and 0.084, respectively). We suggest three reasons for these low scores. First, these analytics require an advanced set of DA skills, such as image processing, dimensionality reduction, and deep learning. Second, feature selection is difficult; currently, selecting significant features from unstructured data such as XCT data of porosity and layer-wise image data of powder layer is still a problem. Third, the required data are collected from multiple data sources. For example, DO_{106} requires data from XCT, layer-wise camera, and process planning software. Data fusion for heterogeneous data is challenging for reasons such as the difficulty in aligning contexts among the data (Shen et al., 2021).

The prioritization matrix of the case study prioritizes DA opportunities; it also indicates the status of DA

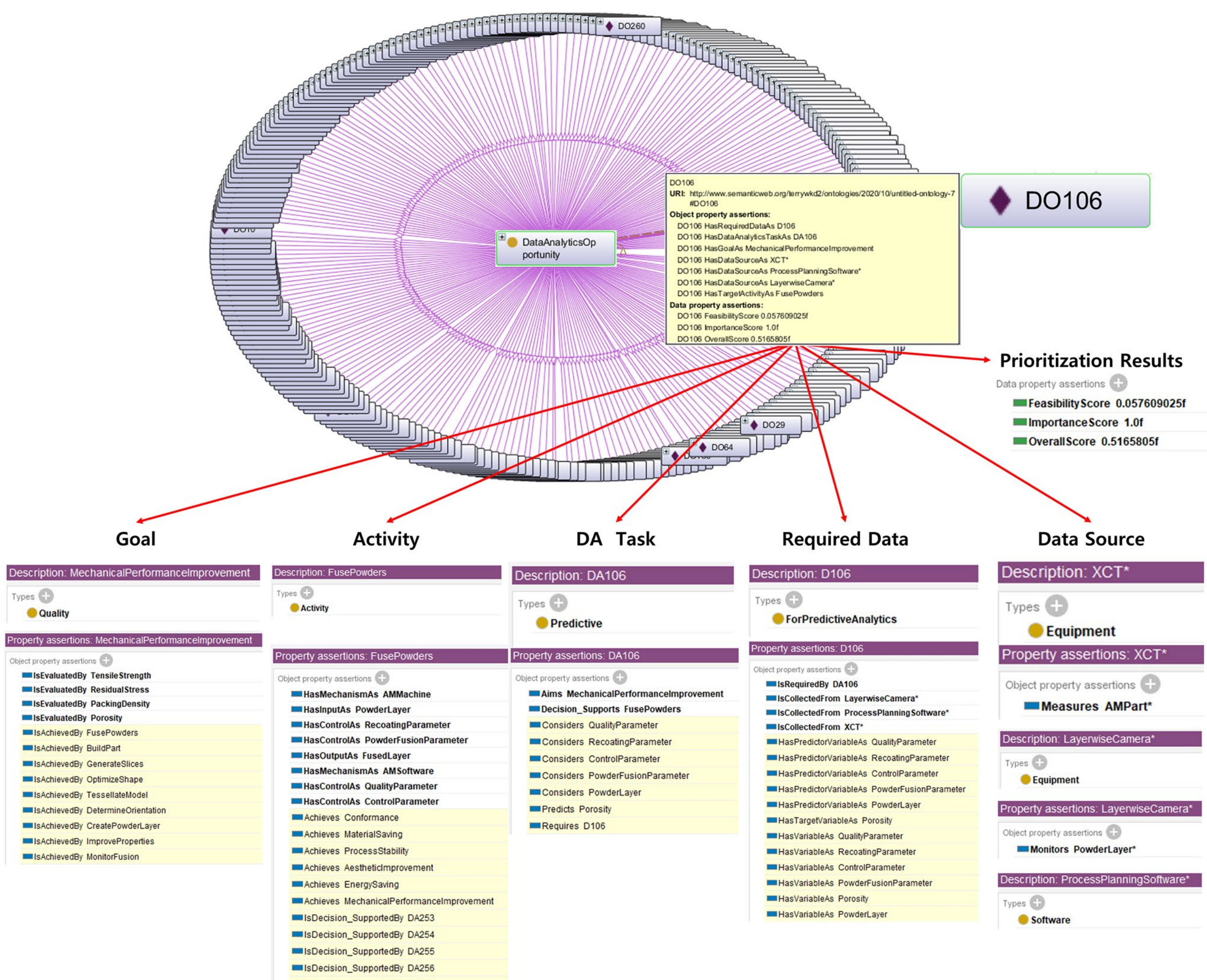

Fig. 9 An example of DA opportunity DO_{106}

Table 3 Linguistic ratings of expertise level of experts with respect to the six criteria

Expert	Benefit criteria			Cost Criteria		
	C_1	C_2	C_3	C_4	C_5	C_6
E_1	SH	SH	H	VH	H	SH
E_2	SH	H	SH	SH	M	M
E_3	VH	H	H	M	SH	H
E_4	H	VH	H	SH	M	H
E_5	VH	VH	H	H	H	VH
E_6	VH	H	H	M	M	H

technology in the L-PBF process. The ICC and FCC scores showed a strong negative Pearson's Correlation Coefficient ($r = -0.695$), which implies that the important DA opportunities have low feasibility. Similarly, the prioritization matrix shows that many DA opportunities belong to the second group (G2), in which the opportunities have high

Table 4 Linguistic ratings of the DA opportunities by the experts

Expert	DA Opportunity	Benefit criteria			Cost criteria		
		C_1	C_2	C_3	C_4	C_5	C_6
E_1	DO_1	SH	H	H	VH	H	SL
	DO_2	SH	H	H	H	SH	SL
	…	…	…	…	…	…	…
	DO_{264}	SH	SH	M	M	L	L
E_2	DO_1	VH	VH	SL	H	M	M
	DO_2	VH	VH	VH	M	M	M
	…	…	…	…	…	…	…
	DO_{264}	VH	L	L	M	H	M
E_3	DO_1	H	H	H	H	SH	SH
	DO_2	SH	SH	SH	SH	SH	SH
	…	…	…	…	…	…	…
	DO_{264}	H	H	H	H	VH	VH
E_4	DO_1	SH	M	SL	SL	SL	L
	DO_2	SH	SH	SH	M	M	H
	…	…	…	…	…	…	…
	DO_{264}	SH	H	H	H	H	VH
E_5	DO_1	SH	H	H	VH	VH	H
	DO_2	SH	H	H	H	H	H
	…	…	…	…	…	…	…
	DO_{264}	VH	VH	VH	M	H	H
E_6	DO_1	H	H	SH	M	M	M
	DO_2	H	H	H	SH	M	M
	…	…	…	…	…	…	…
	DO_{264}	VH	VH	H	H	H	SH

Table 5 The weighted aggregated fuzzy matrix

DA	Benefit criteria			Cost criteria		
Opportunity	C_1	C_2	C_3	C_4	C_5	C_6
DO_1	(144,209,260)	(148,214,273)	(113,171,241)	(118,176,224)	(95,147,204)	(87,139,196)
DO_2	(138,202,253)	(149,215,273)	(139,203,273)	(103,158,218)	(88,139,202)	(107,163,224)
…	…	…	…	…	…	…
DO_{264}	(162,230,267)	(142,206,253)	(124,184,249)	(95,150,212)	(99,155,217)	(123,182,232)

Table 6 The normalized fuzzy decision matrix

DA	Benefit criteria			Cost criteria		
Opportunity	C_1	C_2	C_3	C_4	C_5	C_6
DO_1	(0.53,0.76,0.95)	(0.52,0.75,0.95)	(0.39,0.60,0.84)	(0.25,0.32,0.47)	(0.24,0.33,0.52)	(0.14,0.20,0.32)
DO_2	(0.50,0.74,0.92)	(0.52,0.75,0.95)	(0.48,0.71,0.95)	(0.26,0.35,0.54)	(0.24,0.35,0.56)	(0.13,0.17,0.26)
…	…	…	…	…	…	…
DO_{264}	(0.59,0.84,0.97)	(0.49,0.72,0.88)	(0.43,0.64,0.87)	(0.26,0.37,0.59)	(0.23,0.32,0.49)	(0.12,0.15,0.23)

Table 7 FPIS and FNIS

Solution	Benefit criteria			Cost criteria		
	C_1	C_2	C_3	C_4	C_5	C_6
FPIS	(0.63, 0.89, 1)	(0.61,0.86,1)	(0.59,0.83,1)	(0.38,0.59,1)	(0.33,0.53,1)	(0.24,0.41,1)
FNIS	(0.33,0.53,0.70)	(0.18,0.34,0.52)	(0.24,0.41,0.62))	(0.22,0.30,0.45)	(0.2,0.27,0.41)	(0.10,0.13,0.19)

Table 8 The modified Fuzzy TOPSIS results

DA opportunity	Benefit criteria						Cost criteria						ICC (#rank)	FCC (#rank)	OCC (#rank)
	C_1		C_2		C_3		C_4		C_5		C_6				
	d^*	d^-	d^*	d^-	d^*	d^-	d^*	d^-	d^*	d^-	d^*	d^-			
DO_1	0.17	0.39	0.16	0.68	0.35	0.33	0.61	0.04	0.53	0.13	0.72	0.15	0.675 (#56)	0.146 (#229)	0.405 (#135)
DO_2	0.21	0.35	0.15	0.68	0.17	0.51	0.53	0.11	0.49	0.17	0.78	0.08	0.743 (#41)	0.169 (#222)	0.450 (#77)
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
DO_{264}	0.07	0.49	0.22	0.61	0.28	0.39	0.48	0.16	0.56	0.1	0.82	0.04	0.724 (#49)	0.140 (#231)	0.425 (#111)

Table 9 The case study results for the four prioritization groups

Group ID	Group Name	Conditions	Case Study Result -No. of DA Opportunities	Remark about DA Opportunity
G1	High Importance High Feasibility	ICC > 0.5 & FCC > 0.5	3	Critical
G2	High Importance Low Feasibility	ICC > 0.5 & FCC ≤ 0.5	120	Potential critical; moving some opportunities from G2 to G1 is possible if feasibility is improved
G3	Low Importance Low Feasibility	ICC ≤ 0.5 & FCC ≤ 0.5	117	Negligible
G4	Low Importance High Feasibility	ICC ≤ 0.5 & FCC > 0.5	24	Nonessential

ICC scores but low FCC scores. The reason for the low FCC scores is that there exist technical difficulties that impede the realization of the opportunity. This observation addresses another research topic about how to improve the feasibility of the DA opportunities to promote the opportunities from the second group (G2) to the first group (G1).

Conclusion and Future Work

This paper proposes a methodology that uses the CKM approach to identify high potential and high impact DA opportunities in AM. The methodology has three components: a team of experts, a DOKB, and a prioritization tool. The team of experts provides diverse knowledge that is vital for identifying and prioritizing DA opportunities. The DOKB captures the diverse knowledge to support identification of DA opportunities. The prioritization tool helps prioritize the identified DA opportunities. A case study demonstrated the feasibility of the proposed methodology. It successfully identified and prioritized 264 DA opportunities in the L-PBF process using six experts from NIST. The results revealed the important DA opportunities in the L-PBF process.

The DOKB developed for the case study will continue to be shared, reused, revised, and extended. The shareable and reusable characteristics enable an increasing number of AM users to participate in the CKM to identify or prioritize DA opportunities, thus facilitating the spread of knowledge across the AM industry. New discoveries related to AM business, AM activity, DA, and AM data can be effectively and efficiently used to revise the existing DOKB. For the

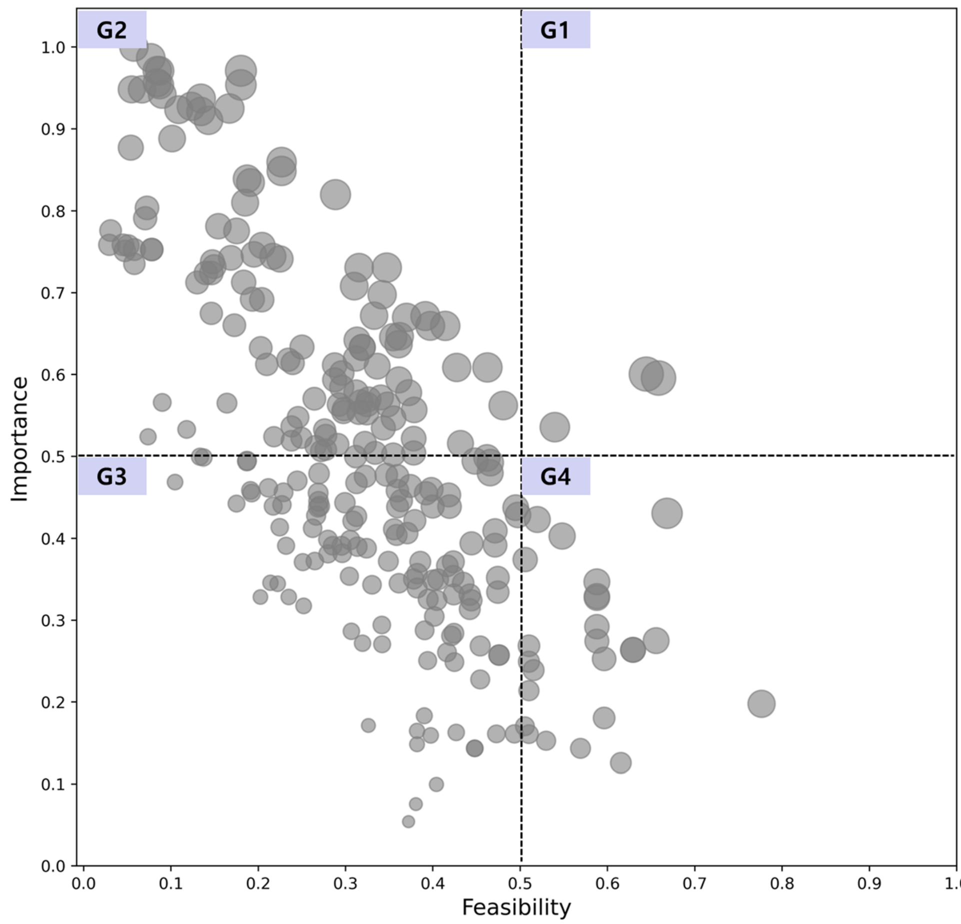

Fig. 10 Prioritization matrix for DA opportunities from the case study

same reason, the prioritization results can be changed if new knowledge addresses DA-related technology, such as sensor technologies, data management technologies, and DA techniques. Furthermore, the DOKB can be extended to include new purposes or approaches.

Our future work will focus on extending the scope of the DOKB to include the realization results of the DA opportunities and recommending DA techniques for realizing the DA opportunities. Once certain DA opportunities are realized, their results—e.g., issues, solutions, performance, and maturity—can be reviewed and stored into the extended DOKB. We plan to automate the process of our CKM approach for improving efficiency. The DOKB can be improved by using ontology-learning techniques to automatically capture required knowledge from experts.

Finally, the proposed methodology can also be applied to other data-intensive manufacturing industries, where identifying important and feasible DA opportunities will contribute to innovations in product quality, productivity, and competitiveness.

Table 10 Example DA opportunities with prioritization results

Group	DA Opportunity	Goal	Target Activity	DA Task	Required Data	Data Sources	ICC (Rank#)	FCC (Rank#)	OCC (Rank#)
G1	DO_{136}	*Material Saving*	*Design Supports*	Characterizes *TheAmountofSupports*	IsRelatedTo *Support Structure*	*Process Planning Software*	0.595 (#81)	0.658 (#3)	0.627 (#1)
G2	DO_{106}	*Mechanical Performance Improvement*	*Fuse Powders*	Predicts *Porosity*	HasTarget VariableAs *Porosity* HasPredictor VariableAs *PowderLayer Quality Parameter* *Control Parameter* *PowderFusion Parameter* *Recoating Parameter*	*XCT* *Layerwise camera* *Process Planning Software*	1 (#1)	0.057 (#257)	0.516 (#24)
G3	DO_{119}	*Mechanical Performance Improvement*	*Improve Properties*	Diagnoses *Residual Stress*	HasResponse VariableAs *ResidualStress* HasExplanatoryVariableAs *AMPart* *HeatTreatment* *Parameter*	*XRD* *Heat Treatment Software*	0.971 (#3)	0.084 (#246)	0.510 (#29)

Appendix

See Table 11, Table 12, Table 13

Table 11 The properties of the classes in Things Defined in the Data Analytics Tier

Property	Subproperty of	Domain	Range
Decision_Supports		DataAnalyticsTask	Activity
Aims		DataAnalyticsTask	Goal
Considers		DataAnalyticsTask	ICOM
Optimizes		Prescriptive	PerformanceIndicator
Maximizes	Optimizes	Prescriptive	PerformanceIndicator
Minimizes	Optimizes	Prescriptive	PerformanceIndicator
Prescribes		Prescriptive	Control
Predicts		Predictive	PerformanceIndicator
Diagnoses		Diagnostic	PerformanceIndicator
Characterizes		Descriptive	PerformanceIndicator

Table 12 The properties of the classes in the Things Defined in the Data Tier

Property	Subproperty of	Domain	Range
IsRequiredBy		Data	DataAnaltyicsTask
HasVariableAs		Data	ThingsDefinedintheActivityLayer
HasDecisionVariableAs	HasVariableAs	ForPrescriptiveAnalytics	Control
HasObjectiveVariableAs	HasVariableAs	ForPrescriptiveAnalytics	PerformanceIndicator
HasBlockingVariableAs	HasVariableAs	ForPrescriptiveAnalytics	ICOM
HasPredictorVariableAs	HasVariableAs	ForPredictiveAnalytics	ICOM
HasTargetVariableAs	HasVariableAs	ForPredictiveAnalytics	PerformanceIndicator
HasExplanatoryVariableAs	HasVariableAs	ForDiagnosticAnalytics	ICOM
HasResponseVariableAs	HasVariableAs	ForDiagnosticAnalytics	PerformanceIndicator
IsRelatedTo	HasVariableAs	ForDescriptiveAnalytics	ICOM

Table 13 The SWRL rules for defining DA tasks and data requirements

SWRL rule (a): For the four types of DA tasks
Prescriptive Analytics Rule 1:
IsEvaluatedBy(?*G*, ?*PI*) ^ IsMeasuredIn(?*PI*, ?*A*) ^ Prescriptive(?*DA*) ^ Aims(?*DA*, ?*G*) ^ Decision_Supports(?*DA*, ?*A*) ^ HasInputAs(?*A*, ?*I*) ^ HasControlAs(?*A*, ?*C*) ^ MonotonePositiveImprovingDirection(?*PI*, true) ^ MonotoneNegativeImprovingDirection(?*PI*, false)—> Prescribes(?*DA*, ?*C*) ^ Maximizes(?*DA*, ? *PI*) ^ Considers(?*DA*, ?*I*)
Prescriptive Analytics Rule 2:
IsEvaluatedBy(?*G*, ?*PI*) ^ IsMeasuredIn(?*PI*, ?*A*) ^ Prescriptive(?*DA*) ^ Aims(?*DA*, ?*G*) ^ Decision_Supports(?*DA*, ?*A*) ^ HasInputAs(?*A*, ?*I*) ^ HasControlAs(?*A*, ?*C*) ^ MonotonePositiveImprovingDirection(?*PI*, false) ^ MonotoneNegativeImprovingDirection(?*PI*, true)—> Prescribes(?*DA*, ?*C*) ^ Minimizes(?*DA*, ?*PI*) ^ Considers(?*DA*, ?*I*)
Predictive Analytics Rule:
IsEvaluatedBy(?*G*, ?*PI*) ^ IsMeasuredIn(?*PI*, ?*A*) ^ Predictive(?*DA*) ^ Aims(?*DA*, ?*G*) ^ Decision_Supports(?*DA*, ?*A*) ^ HasInputAs(?*A*, ?*I*) ^ HasControlAs(?*A*, ?*C*)—> Predicts(?*DA*, ?*PI*) ^ Considers(?*DA*, ?*I*) ^ Considers(?*DA*, ?*C*)
Diagnostic Analytics Rule:
IsEvaluatedBy(?*G*, ?*PI*) ^ IsMeasuredIn(?*PI*, ?*A*) ^ Diagnostic(?*DA*) ^ Aims(?*DA*, ?*G*) ^ Decision_Supports(?*DA*, ?*A*) ^ HasInputAs(?*A*, ?*I*) ^ HasControlAs(?*A*, ?*C*)—> Diagnoses(?*DA*, ?*PI*) ^ Considers(?*DA*, ?*I*) ^ Considers(?*DA*, ?*C*)
Descriptive Analytics Rule:
IsEvaluatedBy(?*G*, ?*PI*) ^ IsMeasuredIn(?*PI*, ?*A*) ^ Descriptive(?*DA*) ^ Aims(?*DA*, ?*G*) ^ Decision_Supports(?*DA*, ?*A*)—> Characterizes(?*DA*, ?*PI*)
Where: *G*: Goal instance, *PI*: Performance indicator instance *A*: Activity instance, *DA*: DA task instance, *I*: Input instance, *C*: Control instance
SWRL rule (b): For the four types of required data
Prescriptive Analytics Data Requirement Rule:
IsRequiredBy(?*D*, ?*DA*) ^ Prescriptive(?*DA*) ^ Considers(?*DA*, ?*X*) ^ Optimizes(?*DA*, ?*PI*) ^ Prescribes(?*DA*, ?*C*)—> HasDecisionVariableAs(?*D*, ?*C*) ^ HasObjectiveVariableAs(?*D*, ?*PI*) ^ HasBlockingVariableAs(?*D*, ?*X*)
Predictive Analytics Data Requirement Rule:
IsRequiredBy(?*D*, ?*DA*) ^ Predictive(?*DA*) ^ Predicts(?*DA*, ?*Y*) ^ Considers(?*DA*, ?*X*)—> HasPredictorVariableAs(?*D*, ?*X*) ^ HasTargetVariableAs(?*D*, ?*Y*)
Diagnostic Analytics Data Requirement Rule:
IsRequiredBy(?*D*, ?*DA*) ^ Diagnostic(?*DA*) ^ Diagnoses(?*DA*, ?*Y*) ^ Considers(?*DA*, ?*X*)—> HasExplanatoryVariableAs(?*D*, ?*X*) ^ HasResponseVariableAs(?*D*, ?*Y*)
Descriptive Analytics Data Requirement Rule:
IsRequiredBy(?*D*, ?*DA*) ^ Descriptive(?*DA*) ^ Characterizes(?*DA*, ?*X*)—> IsRelatedTo(?*D*, ?*X*)
Where: *D*: Data instance, *DA*: DA task instance, *PI*: Performance indicator instance, *C*: Control instance, X,Y: Parameters

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