Quality of Measurement Information in Decision-Making

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***Abstract*—This article introduces a general-purpose framework aimed at capturing the elusive concept of quality of measurement information (MI), a critical issue for both researchers and practitioners when dealing with MI-enabled decision-making. The framework is a blueprint for the definition, assessment, communication, and improvement of MI quality, as analyzed through a set of general criteria, classified according to the syntactic, semantic, and pragmatic layers of semiotics, as suggested in the ISO 8000-8:2015 technical standard. The top-down analysis, where each criterion is specified in terms of characteristics and each characteristic in terms of domain-related indicators, is complemented with a bottom-up synthesis and operationalized by means of a flowchart. An application example, about the quality of information provided by the networks of measurement instruments reporting pollutants in the air, is presented to test the usefulness and the limitations of the framework.**

***Index Terms*—Decision-making, measurement, measurement information (MI), quality management, semiotic criteria, semiotics.**

Nomenclature

IEDM	Information-enabled decision-making.
MI	Measurement information.
QoI	Quality of information.
QoMI	Quality of measurement information.

I. Introduction

IN TODAY'S information society, data rule transformative technologies, and with them the social and economic progress, thus assuming a role analogous to the one that oil had in the industrial society: a valuable resource, and a key enabler for almost everything, from governments, to companies, to everyday activities. Without data, development would be hampered, and economies would shrink.

In the last years, increasing amounts of data from both the empirical world and the internet have been indeed acquired, transmitted, and stored, often at very low (and sometimes zero marginal) cost, by means of digital systems. This is epitomized by the concept of big data, which has been spreading among the experts and the general public despite its vagueness; it broadly refers to any sufficiently large data set, or collection of data sets, usually heterogeneous (e.g., text, audio, images, and video) and sometimes so poorly structured that it is difficult to effectively deal with them with the traditional methods and tools of computer science and statistics.

However, like oil that needs to be transformed into valuable goods (such as gasoline and plastic), data need to be transformed into useful information for effectively supporting decision-making processes, toward what may be called Information-enabled Decision-Making (IEDM) [1]. As a scientific field, IEDM has no sharp boundaries and the related literature is huge, as most (in particular supervised) data mining and machine learning techniques may be interpreted as tools for prediction and decision-making based on data [2].

Conservatively, big data are supposed to reduce the probability of wrong decisions [3], but the bold hypothesis has also been proposed that "the data deluge [will make] the scientific method obsolete," thus marking "the end of theory" because "with enough data, the numbers speak for themselves" [4]. We stand here on the more conservative side and consider data as necessary but generally not sufficient for effective decision making. For this reason, we refer to situations in which the process of making decisions is enabled, but not driven, by information: what instead should drive the process is the knowledge of the object of the decision and of the purpose of the decision itself. The procedural definition of the entire process would then require the formalization of such a broad context, which is not the purpose of this article.

Rather, our focus here is on Quality of Information (QoI). Independently of available amount of data and whichever the goals, the so-called garbage-in garbage-out principle applies, i.e., poor information quality may lead to wrong decisions, with potentially severe undesirable consequences: QoI is then a crucial factor for assuring effective IEDM processes [5]–[9].

Unfortunately, the massive proliferation of data sources and the exponential growth in data volumes that characterize big data can make QoI hard to assess and even harder to assure. This is worsened by the emergence of highly distributed, heterogeneous data, and multiadministrative application deployment paradigms for sensor-and-actuator networks, such as the Internet of Things (IoT) [10], [11]. In addition, these paradigms include fast-paced machine-to-machine applications that challenge timescales and make the role of QoI even more critical than in traditional human-controlled IEDM processes.

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The capability to properly manage QoI is then imperative, and this explains the vast literature on this topic in the relevant fields and the significant amount of resources dedicated to quality issues in big data systems [12]–[14].

However, to the best of the authors' knowledge, papers dealing with the quality of the information produced by and associated with measurement—called here Quality of Measurement Information (QoMI)—are virtually lacking despite the growing relevance of the topic due to the widespread diffusion of data-generating devices, in industrial automation, health care systems, environmental protection, ambient intelligence and surveillance, domotics, and so on. This may be because research in instrumentation and measurement is focused on high-tech laboratory measurement where many conditions affecting QoMI are well known and can be controlled. The consequence is the usual position that measurement uncertainty effectively summarizes everything that is relevant to QoMI.

Conversely, the devices that, outside the labs, produce data from the empirical world are often designed and operated focusing on their functional performance, while their metrological characterization (and consequently the quality of returned information) is of minor relevance [1].

Unlike the instrumentation and measurement field, computer science and engineering have developed a huge amount of literature about the quality of (generic) information that is available, but the problem is not analyzed from a metrological perspective. This is a serious gap, and this article aims at contributing to fill it. In particular, we will argue that several other factors, together with measurement uncertainty, need to be considered to ensure that the information provided by measurement "fits for purpose": in such a broader context, whether a measurement is "good" or "bad" depends on its ability to produce information that effectively supports IEDM processes [1], and measurement uncertainty is only a component, though usually a critical one, of such an ability.

This article introduces a conceptual and operational framework aimed at identifying several components of the IEDM-oriented QoMI. The framework accompanies its user in this endeavor through a top-down analysis, in which the complexity of a decision-making problem is acknowledged as affected by the compresence of multiple criteria, where each criterion is specified in terms of characteristics, which are then operationalized by means of domain-related indicators, whose ranges of acceptable values are derived from context-dependent requirements. This analysis offers a structured understanding of QoMI and allows the user of the framework to assess whether the quality of the available information is sufficient for supporting IEDM. The complementary bottom-up process of synthesis, which leads to an actual decision, is so dependent on contextual and pragmatic factors (including the level of specification of the target) that hardly can be supported by a general-purpose tool, and in any case, this is not the purpose of the framework we present here. The several stages of top-down analysis and bottom-up synthesis are also presented by means of a flowchart.

In summary, measurement is expected to produce not only values of the measurand but also information about the trustworthiness with which such values are attributed to the measurand. This contributes to the QoMI, so as to make it possible to distinguish "good" (i.e., able to produce information that is useful for the intended purpose) from "bad" measurements. Hence (i) the possibility to evaluate such quality is critically important for appropriate design and performance evaluation of a measurement; (ii) ideally, QoMI should be then measured in turn, a challenging task given its complexity and the diversity of the contexts in which it is applied; and therefore (iii) a framework that supports the collection and the organization of QoMI may be useful to this endeavor.

This article is organized as follows. Section II characterizes the complex concept of information in the context of semiotics, which in Section III is applied to the case of measurement. Section IV describes the concept of QoMI. Section V introduces a general-purpose QoMI-oriented framework by describing its structure and identifying some of its characterizing criteria. Section VI illustrates the use of the framework by means of an application example. Section VII discusses how this work relates to the literature in the topic, and Section VIII highlights the main limitations of the framework and suggests possible research directions. Some final remarks are drawn in Section IX.

II. Syntactic, Semantic, and Pragmatic Information

What is information is a complex issue: "there is a network of related concepts of information, with roots in various disciplines such as physics, mathematics, logic, biology, economy, and epistemology" [15]. In particular, in the context of big data, information and data are sometimes intermingled, whereas some authors consider them to be distinct entities [12], [16]. We frame our understanding of QoMI in a semiotic perspective, which provides a hierarchical structure for the definition of information, and split into three layers traditionally called "syntactic," "semantic," and "pragmatic," related, respectively, to the form, the meaning, and the usefulness of the signs that vehicle information [17].

The first layer only requires that a set of elements is given, possibly together with some conditions of comparison and rules of combination among the elements. The selection of an element from the set provides the most fundamental kind of information; we are informed that that element has been selected, instead of any other of the set. Despite its simplicity, this standpoint proved to be very effective in grounding the first full-fledged mathematical theory of transmission [18] and from then on in providing a criterion for measuring the quantity of information in bits (if the set contains two equiprobable elements, the selection of one of them conveys 1 bit of information and so on). As considered in this layer, information is syntactic, being referred to "the formal relations of signs to one another," in the words of Morris [17]. This has to do with a common use of the term "data," and accordingly, we will use "data" and "syntactic information" as synonyms here. Data as such are purely formal entities, whose treatment—storage, retrieval, transfer, and also processing, whenever the rules of combinations are explicitly specified—does not depend on the meaning(s) that someone might associate with them (what data are is an elusive question, with different positions; for example, ISO 9000:2015 defines it as "facts about an object" [19], thus making the related concept not purely syntactic).

However, we usually acquire and manage data with a purpose, not to perform a purely syntactic activity (like instead, it occurs in a game-like chess, in which player proficiency has nothing to do with interpreting K as a king, Q as a queen, and so on). Despite the wealth of results obtained at the syntactic layer—to which the two fundamental Shannon's theorems about source entropy and channel capacity paved the way [18]—human interest is usually for data as carriers of meanings. Meaning is attributed to data by referring each element of the set to something else outside the set itself, which represents the context in which data are produced. Associating data with metadata is the simplest formal technique to embed them in a semantic context. This merges data into a second layer, in which the emphasis is on "the relations of signs to the objects to which the signs are applicable" [17]. Data equipped with meanings become semantic information.

The third layer builds upon this and adds the context in which data-with-meaning are used by some agents for some purposes, where such fitness for purpose is sometimes called the "value" of data. Indeed, the same syntactic entity, e.g., the string "no," once equipped with a meaning, e.g., negation in English, and thus made a semantic entity, may have very different values (compare receiving a "no" to the questions "have you already read my draft?" or "is all quiet on the western front?": quite a critical difference for most persons, though syntax and semantics are exactly the same). Such an encompassing perspective is then about "the relations of signs to the interpreters" [17], and it refers to pragmatic information, which relates to the user's interpretation of signs and depends on the user's *a priori* knowledge.

It could be noted that while the quantity of syntactic information is comprehensively dealt with in Shannon's framework, only hypotheses have been advanced about the quantification of semantic information [20]–[23], and we are not aware of any general solution proposed for the quantification of pragmatic information and, therefore, for attributing a (formal) value to the (pragmatic) value of information.

For the goals of the present work, it is particularly interesting that each of these three layers has its own quality criteria.

- The quality of syntactic information is about the consistency with the formal rules characterizing the set from which data are selected.
- The quality of semantic information is about the correctness of the meanings associated with data, and thus, whenever this applies, to their truth, intended as the correspondence between the semantized data and the actual state of the world [24].
- The quality of pragmatic information is about the relevance and the usefulness in the use context of the semantized data.

This layered structure offers a significant insight also about the conditions for the social role of information, where at each layer the information producer and the information user have to agree on the prerequisites needed for effective information sharing:

- at the syntactic layer, a common set of elements, or a rule for mapping distinct sets to one another, and a common set of formal rules of data treatment;
- at the semantic layer, a common set of meanings or a rule for recognizing the compatibility of meanings expressed in different ways, as in a linguistic context that is provided by a common vocabulary, i.e., a set of terms and definitions, possibly together with a multilingual dictionary;
- at the pragmatic layer, a common set of criteria for agreeing upon the value of the semantized data for the decision to be made.

In each layer, there could be a divergence—a gap—between the information delivered by the producer and that received by the user: if this occurs, the effectiveness of the exchange of information between the producer and the user may be compromised.

Fig. 1 summarizes these key aspects of the semiotic understanding of information.

III. Measurement Information

Measurement is a process aimed at producing information and, as such, can be interpreted in a semiotic perspective both at a fundamental level [25]–[29] and in specific application fields [30], [31], and this in turn provides us with a structured context for discussing about QoMI. As a preliminary assumption, let us consider that the empirical world consists of objects (physical bodies, phenomena, events, processes, individuals, organizations, and so on) that have properties (we are usually adopting here the terminology of the International Vocabulary of Metrology [32]). Relevant to measurement is information about properties, and more specifically quantities, of objects: measurement results are in fact information elements in the form of values, attributed to the quantity intended to be measured, i.e., the measurand, or characterizing other relevant properties, of the object under measurement, the measuring system, and the environment in which they are embedded. The three layers of semiotics provide an effective interpretation of MI as follows, in reference to the simple example of the measurement of the temperature of a liquid in a container by means of an alcohol thermometer (for an extended presentation of this measurement model, see [33]).

- *Syntactic Layer*: As the result of its thermal contact with the liquid, the alcohol expands in the tube of the thermometer and its upper surface reaches a position that corresponds to a mark on the scale etched on the instrument; if at first nothing is assumed on what caused the transduction, the instrument indication, i.e., the value of position associated with the mark, is purely syntactic information, being only about the fact that among the possible indications one is selected as the result of the transduction. Instrument indications as such are then measurement data, which may be treated (i.e., stored, transmitted, compared, and so on) still with no reference to the temperature that produced them. While stopping

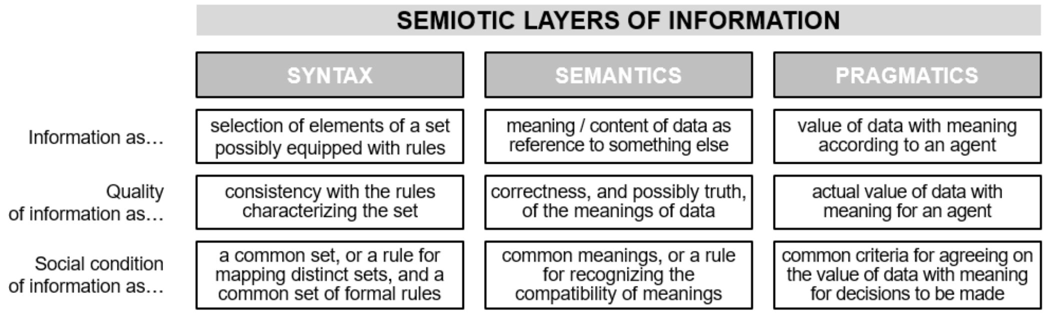

Fig. 1. Summary of the semiotic layers of information.

at this stage may appear an artificial condition in the considered example, such a situation might not be so unusual in the context of big data if data sets are stored and made available without accompanying metadata. The basic information elements in the syntactic layer are then the instrument indications.

- *Semantic Layer*: The semantization of measurement data is about interpreting them as conveying information on the measurand. It requires the adoption of a model of the transduction and the physical context of measurement (and therefore the metrological characterization of the behavior of the instrument, including the identification of the relevant quantities other than the measurand that influence the instrument behavior) and the adoption of a model of the measurand (leading to establish the uncertainty related to the very definition of the measurand, the so-called “definitional uncertainty” [32]), and then the functional connection of the instrument with a primary standard that realizes the definition of the relevant unit (i.e., of the temperature in the considered example) and enables the instrument calibration via a metrological traceability chain. This transforms the instrument indication into a measurement result, then equipping measurement data with a semantic component, due to the fact that instrument indications are referred to the measurand via the instrument calibration, which provides a context to the transduction performed by the instrument. The basic information elements in the semantic layer are then the values attributed to the measurand, together with the values of all other properties involved in the process: the influence quantities, the quantities affecting the measurand itself, and the quantities embodied in the measurement standards, all of them explicitly or implicitly accompanied by the values of their uncertainty, as reported in the so-called “uncertainty budget” [32].
- *Pragmatic Layer*: The measurement result contains, in some form, information of both location and dispersion of the measurand, for example, as a pair (measured value and standard measurement uncertainty). The core information about the purpose of measurement is encoded in target uncertainty, “specified as an upper limit and decided on the basis of the intended use of measurement results” [32]. If the measurement uncertainty is less than the target uncertainty, the measurement result is considered to be useful to support decision-making, and this embeds measurement in the pragmatic layer. While the basic information element in the pragmatic layer is then the value of the target uncertainty, all criteria relevant to the IEDM process (see Table I) concur to form the information elements of this layer.

In summary, transduction as such can be modeled as a syntactic process: in the example proposed above, what we read on the thermometer scale still without reference to the measured temperature is syntactic information. Measurement is a semantic process, aimed at evaluating the relationship between the measurand and the measurement scale, and the measurement results are then semantic information. Finally, measurement IEDM is a pragmatic process, in which measurement results are key (though not exclusive) enablers for decision making. Fig. 2 extends Fig. 1 and adapts it to the case of measurement.

This semiotic understanding of measurement could be further developed, in particular for considering that some information on the measurand is available before measurement (possibly quantified as a definitional uncertainty), so that the value of measurement might be characterized in reference to the differential (prior versus posterior) pragmatic information that it conveys, and that measurement uncertainty is inversely related to the semantic information conveyed by a measurement result, so that the greater the uncertainty the less the conveyed information. However, even this simple introduction is sufficient to show that the fundamentals of semiotics may be extended beyond human communication and can provide an effective conceptual framework for identifying, describing, and analyzing the relevant aspects of QoMI.

IV. Quality of Measurement Information

The concept of quality of an entity (a process, a product, a service, and so on) is complex and has been defined in different ways in the literature. Only referring to a significant sample of relevant technical standards, the definition proposed in the ISO 9000 series—“degree to which a set of inherent characteristics of an object fulfills requirements” [19]—effectively gets the point: quality has to do with fulfilling requirements. A bit less generic is the definition of (the more specific concept) “data quality” in the ISO/IEC

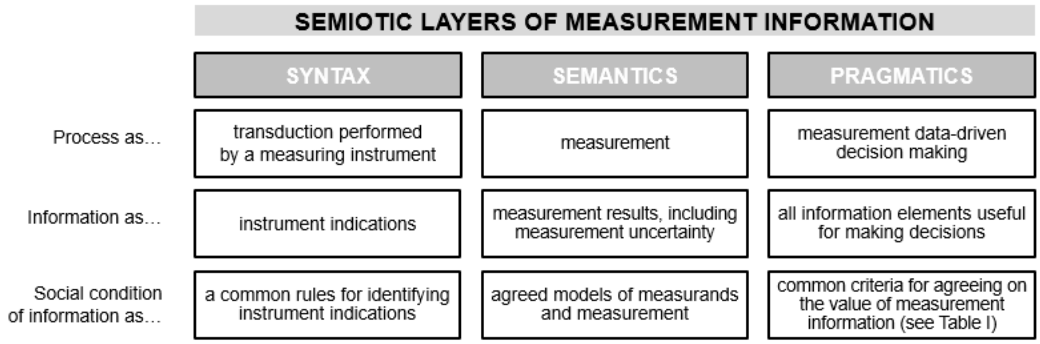

Fig. 2. Summary of the semiotic layers of information in the case of measurement.

25000 series of standards on Software product Quality Requirements and Evaluation (SQuaRE): "degree to which the characteristics of data satisfy stated and implied needs when used under specified conditions" [34]. In the perspective of interpreting and adapting these definitions to QoMI, two key aspects of the concept may be elaborated for making these definitions more explicit: the kind of requirements/needs and the role of information producers and users.

The first point is clear: quality has to do with requirements, and without requirements, there cannot be quality (nor non-quality in fact). It is in reference to requirements that a primary classification is introduced between "internal" and "external" quality: though not uniquely interpreted, this distinction is usually about a more specific and a more encompassing understanding, where internal quality is typically related to conformity to specifications and external quality is about fitness for use. The latter implies that the intended users of the entity whose quality is under evaluation are identified and their needs specified.

Regarding the roles of producers and users, when the measurement is of concern multiple roles are involved, in particular, the designers of the measurement process, who choose the method, the procedure, and the measuring system in consequence (for a definition of these concepts, see [32]), those who perform the measurement, including both its empirical and informational components, the regulators or third-party auditors who have the task of validating the process, the decision makers who, under the condition that measurement results are pragmatically appropriate, use them as key supporting elements of their conclusions, and finally the end users of the measurement result, who in some cases are the society at large (as occurs, for example, with measurements for environmental protection). Each of these categories of producers/users has its own, stated or implied, needs: the key objective of QoMI evaluation and management is then to meet, and possibly to anticipate, such diverse needs and expectations [7], [16], [35].

A precondition for an appropriate of QoMI evaluation and management is that common syntactic and semantic information is shared among its relevant producers/users, with the fundamental aim of ensuring its intersubjectivity [36], [37]. Specifically, "measurement cannot be adequately characterized solely using a black-box model: if a given attribution of value(s) to a property is claimed to be a measurement result (instead of, e.g., a guess), it must be possible to explain how it was obtained, by "opening the box" and identifying the features of the process that secure the quality of the results." [38]. However, it is worth observing that MI producers do not need to provide perfect quality, but they are required to be explicit about the level of quality they provide, with the awareness that it should be chosen in dependence on user's needs.

As for the concept 'fitness for use,' while it captures the essence of what quality is, it hardly allows us to evaluate quality, given its too broad and ambiguous definition and the multitude of aspects that it normally includes. Thus, to enable QoMI evaluation and management, the multidimensionality of fitness for use has to be analyzed from the perspectives of the different producers/users, by identifying the properties of the entity that are relevant to fulfill the identified requirements and checking whether the values of such properties are in the acceptance ranges derived from requirements. The basic assumption is that properties perfectly satisfying requirements are the most effective so that poor quality relates to excessive deviations of the property values from those needed to fulfill requirements. Unfortunately, in practice, some needs may remain unidentified because they are not expressed or may change with producers/users' knowledge and experience. As a consequence, we have to distinguish between the component of quality related to identified needs, called here modeled quality, and the component that reflects implied, unidentified needs, called latent quality [14], [35]. Clearly, only the modeled component can be effectively managed, and what follows only covers the related explicit aspects of the MI fitness for use.

Furthermore, in the perspective of QoMI evaluation and management, it is important to distinguish two situations that may occur in practice. They are about the relationship between MI and IEDM, which can be [3] and [22] (cap. 15):

- *Strongly Coupled*: This situation occurs when the measurement is specifically designed to fulfill the information needs of a specific IEDM; in this case, the purposes for which MI is produced (p-purpose) and used (u-purpose) coincide.
- *Loosely Coupled*: This situation occurs when MI has been produced to fulfill information needs that differ from those of the user (i.e., p-purpose and u-purpose differ from each other), and MI is repurposed *ad hoc*; this

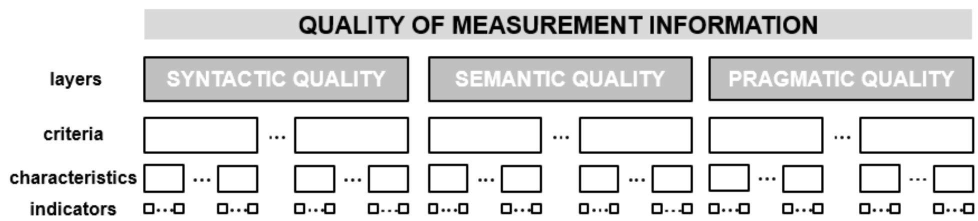

Fig. 3. Hierarchical structure of the proposed framework for MI quality.

case is quite common since measurements often provide information that can be repurposed.

When MI and IEDM are strongly coupled, the measurement system designer is expected to know *a priori* (i.e., before the design) the user's information needs. In that context, the QoMI is determined by the designer's capability of linking the user's needs to MI characteristics, which in turn depends on the adopted measurement system performance [36]. The situation is very different when MI and IEDM are loosely coupled and the user's information needs are unknown at design time. As an example, if a new general-purpose sensor network for industrial machine monitoring is designed, information needs for a specific application and the particular usage context may not be known in advance. In these cases, the user acts as a chooser and he/she achieves optimal "fitness for use" by prioritizing and selecting the available information according to specific, possibly subjective, criteria. Thus, in this situation, quality is related not only to conformance to requirements but also to a variety of available information (assuming that it is not so large to challenge the user selection capabilities) and the extent of its range of validity.

In practice, a combination of the two situations described above often occurs, and quality assessments involve MI properties variation (i.e., deviations from acceptable values), as well as their variety and range of validity.

Given this complexity, one might well conclude that, despite its critical importance, the quality of measurements remains an imponderable property, whose evaluation unavoidably includes informal and subjective components: in short, the QoMI is not measurable. While surely acknowledging that the path that leads to make QoMI a measurable property is long, we claim that a framework, such as the one proposed in Section V, is a useful tool to begin such a path.

V. QoMI Framework

The framework we propose here can be useful to both researchers and practitioners to identify and assess QoMI. It is structured through a set of general-purpose quality criteria, i.e., aspects along which judgments about the fitness for use of MI can be carried out [22, Ch. 14], [29], [34]. As shown in Fig. 3, criteria are classified according to the three layers of semiotics: syntax, semantics, and pragmatics. Each criterion enables the identification of one or more characteristics, which are then operationalized and evaluated by means of one or more domain-specific indicators (often called metrics in the computer engineering field) whose range of acceptable values is derived from user's requirements and whose definition may include the information elements. For example, considering a possible "domain integrity" criterion, a characteristic can be the presence of missing data and a related indicator can be the percentage of missing data.

Observe that the proposed framework lists only general-purpose criteria. It does not include the definitions of characteristics and indicators shown in Fig. 3, as details on these two other substructures are related to operationalization procedures and are usually domain-specific.

The framework is also a QoMI metamodel that can support effective identification and communication of information needs, quality-related defects, causes, and consequences of defects, so enabling information quality improvement. Using the framework, a QoMI tailored to a particular IEDM problem can be obtained by both omitting some criteria that do not fit with the situation at stake or including new specific criteria believed relevant. For generality, we assume that the IEDM problem may require the measurement (or in some cases more generally the evaluation [33]) of several properties, and therefore the multiple measurement results may be exploited to support the IEDM process, where the framework supports the process of taking the information acquired on such "intermediate" measurands into account and combining it to produce a measurement result for the "final" measurand.

The framework is finally operationalized as a procedure that develops in a top-down analysis, leading to the identification and the evaluation of a set of relevant domain-related indicators, complemented with a bottom-up synthesis.

A. Framework Criteria Identification

The identification of the QoMI criteria was based on an extensive review and analysis of papers about QoI, published mainly in the fields of computer science and computer engineering. It is worth noticing that no consensus emerges in the literature on what constitutes a good set of QoI criteria or even on the names assigned to criteria (e.g., different authors associate different meanings to the same name) [29], [34], [35]. Thus, in order to identify a consistent framework, the various criteria found in the literature were analyzed, reorganized, and redefined according to the authors' knowledge in the instrumentation and measurement field, according to the following principles.

- Criteria should be general, i.e., applicable across different application domains.

- Criteria should be clearly defined; their names should be unambiguous, easy to understand, and intuitive, i.e., corresponding as closely as possible to common usage.
- The set of criteria should be comprehensive, i.e., all aspects of QoMI that can be relevant for a generic IEDM activity should be included.
- Criteria overlapping should be minimized; in particular, redundant criteria should be avoided.

The obtained general-purpose criteria were then clustered into the three semiotic layers described in Sections II and III, as also suggested in the ISO 8000-8:2015 standard [29]. Of course, the proposed framework should be considered only as a possible basic, partial, and flexible structure that needs to be tailored to a specific usage: criteria and characteristics not included in the proposal may be relevant for a given IEDM problem. Conversely, some criteria may be unnecessary for specific user's needs.

B. Framework Criteria Definition

The general-purpose QoMI criteria belonging to each semiotic layer are reported in Table I and shortly discussed in the following.

1) Syntactic Quality: Syntactic quality is the degree of integrity and usability of instrument indications for producing measurement results. Relevant general-purpose syntactic criteria are as follows.

- Domain integrity, the degree to which MI is reported with values belonging to the scales of instrument indications and with no missing values. While, in traditional applications, MI and IEDM are strongly coupled and instrument indications are immediately available and, therefore, domain integrity is not usually a problem, in big data contexts, data sets might origin from noisy situations, in which data corruption is possible.
- Indication scale resolution, the degree to which MI allows the detection of small changes in the instrument indications. For instruments with analog indication, scale resolution is also related to the error of indication. Conversely, for instruments with digital reading indication, scale resolution is basically determined by the number of displayed digits.

Syntactic quality assessment is performed by comparing MI characteristics with the corresponding requirements, thus detecting corrupted data. It is a completely objective process, usually performed by current data quality management systems. Its effectiveness depends also on the quality of the adopted syntactic rules that may need to be updated, for instance, using time- or event-based updating policies.

2) Semantic Quality: Semantic quality is the degree of trustworthiness of measurement results in providing an accurate description of both the measurand and the measurement context. Thus, it ensures the credibility customarily associated with MI [1], [22], which may be (inversely) summarized by measurement uncertainty, "parameter, associated with the result of a measurement, which characterizes the dispersion of the values that could reasonably be attributed to the measurand" [39]. The overall measurement uncertainty (called combined standard uncertainty by the GUM) can be obtained as a suitable combination of the contributions associated with relevant general-purpose semantic criteria as follows.

- Object identification, the degree to which MI is univocally referred to the objects under measurement and not to other objects in the empirical context. The widely used indicators associated with this criterion are the detection probability (i.e., the probability of correctly detecting the objects under measurement) and the false alarm probability (i.e., the probability of wrongly declaring an object identification).
- Measurand identification, the degree to which MI is about the measurands and therefore is independent of other properties in the empirical context, called "influence properties," which may affect the behavior of the measuring instrument. An indicator of immunity of a measuring instrument from influence properties is called in some contexts, selectivity, which contributes to instrumental uncertainty [32].
- Intersubjectivity, the degree to which MI has a meaning that is unambiguously interpretable by all potentially interested persons. Metrological systems, and in particular the traceability chains that allow the calibration of measuring instruments, have the fundamental purpose of guaranteeing the intersubjectivity of measurement results [37]. The level of intersubjectivity of a measuring instrument assured by calibration is expressed by the so-called calibration uncertainty. Observe that intersubjectivity is strictly related to the user knowledge. In particular, this criterion requires the user awareness about the meaning of the kind of property and measurement unit [29] involved in MI.
- Measurement scale resolution, the degree to which MI allows the detection of small changes in the measurand. This derives from some basic features of the measuring instrument, including its sensitivity and its resolution [32]. A common indicator for this criterion is the smallest change of the measured quantity that causes a perceptible change in the measuring instrument indication.
- Context awareness, the degree to which MI provides an effective description of the empirical context in which measurement is performed. Such a description usually consists in a model of the context as characterized by the values of some identified influence properties and the relationships describing the mutual interactions between these properties [40]. This criterion allows measurement and IEDM contexts alignment and it ensures measurement verification and reproducibility.
- Domain consistency, the degree to which MI conforms to property-related domain conditions. Some examples are the coherence with the range of admissible values (e.g., only positive values are allowed for length measurement), the coherence between measurement values of mutually related properties (e.g., simultaneous

TABLE I
QoMI FRAMEWORK: SYNTACTIC, SEMANTIC, AND PRAGMATIC GENERAL-PURPOSE CRITERIA

SEMIOTIC LAYERS AND RELATED CRITERIA	**EXPLANATION**: degree to which measurement information (MI) …
SYNTACTIC QUALITY	… conforms to integrity rules related to instrument indications (meaning and value of MI are still not considered)
Domain integrity	… is reported with values belonging to the scales of instrument indications and with no missing values
Indication scale resolution	… allows the detection of small changes in the instrument indications
SEMANTIC QUALITY	… provides a trustworthy representation of the measurand; it pertains to the meaning of instrument indications as interpreted by the MI producer (value of MI is still not considered)
Object identification	… is univocally referred to the objects under measurement
Measurand identification	… is about the measurand, and therefore is independent of influence properties
Intersubjectivity	… has a meaning that is unambiguously interpretable by all intended users
Measurement scale resolution	… allows the detection of small changes of the measurands
Context-awareness	… provides an effective description of the empirical context in which measurements are performed
Domain consistency	… conforms to property-related domain conditions
Time consistency	… is coherent between repeated measurements of the same property
Conciseness	… is free of useless or misleading content (e.g., non-significant digits or a uselessly high reporting rate)
PRAGMATIC QUALITY	… fulfills the requirements of the IEDM problem; it pertains to the value of measurement results as interpreted by the MI user; it depends on user's knowledge and IEDM context
Specificity	… is sufficiently specific to support IEDM because measurement uncertainty is less than target uncertainty
Relevance	… is relevant to support effectively IEDM
Sufficiency	… includes all components required to support IEDM
Confidentiality	… is accessible only by authorized users
Security	… is protected against unauthorized access, use, corruption, damage, or modification
Timeliness	… is available to users within the time intervals required by IEDM
Accessibility	… is easily and quickly retrievable by authorized users
Immediate usability	… can be used directly to support IEDM, without a need of organizing or pre-processing it

measurement of voltage, current, and resistance of a resistor), and the conformance to the ranges of admissible values for the properties of the measurement context (e.g., values for position coordinates, time, and influence properties).

- Time consistency, the degree to which MI is coherent between repeated measurements of the same property or between measured values of mutually compatible properties. Instrument stability affects instrumental uncertainty, which is the basic indicator associated with this criterion.
- Conciseness, which is the degree to which MI is free of useless content that could challenge the user's interpretation (e.g., nonsignificant digits or a uselessly high reporting rate).

Like syntactic quality, also semantic quality assessment can be performed through objective processes. Moreover, it relies on metainformation related to the employed measurement system and its behavior (e.g., information about instrument calibration and operating conditions). Anyway, semantic quality assessment involves some degree of subjectivity in which modeling of the object under measurement and the measurement context depends on measurement purpose [36], [40].

3) Pragmatic Quality: Pragmatic quality is the degree of usability of measurement results for supporting IEDM processes and is generally affected by both user knowledge and IEDM context. Examples of standards dealing with pragmatic QoMI are [41] and [42], in which procedures considering the effect of measurement uncertainty on the probability of wrong decision are given. The relevant general-purpose pragmatic criteria are as follows.

- Specificity, the degree to which MI is sufficiently specific to support IEDM because measurement uncertainty is less than target uncertainty [32].
- Relevance, the degree to which MI is relevant to support effectively IEDM activity. Assessment of relevance requires user's knowledge about the significance of the kind of property involved in the IEDM problem at stake. Relevance may also exhibit location and time depending aspects.
- Sufficiency, the degree to which MI is meaningful and covers all aspects needed to support IEDM. Its assessment requires the user's knowledge about the different aspects involved in the IEDM problem. Of course, when the measurement result is about a measurand derived from multiple "intermediate" measurands, sufficiency applies only to the "final" measurand.
- Confidentiality, the degree to which MI is accessible only by authorized users. In particular, information is fully disclosed when anyone with standard knowledge levels can access to it using wide available technology.
- Security, the degree to which MI is protected against unauthorized access, use, corruption, damage, or modification.
- Timeliness, the degree to which MI is available to the user within the time intervals required by IEDM. Indeed, information available at the wrong time is of no value or it may lead to wrong conclusions (e.g., suitable constraints on measurement reporting rate need to be satisfied when dealing with dynamic systems). Usual timeliness characteristics are: latency, defined as the delay between the time when the measurement is performed and the time when information is available to the user; currency, which is related to the time elapsed from the conclusion of measurement execution; and volatility or obsolescence, which expresses the duration of information meaningfulness. Timeliness is also relevant to the concept of real time, according to which MI must be always (hard real time) or mostly (soft real time) available within predefined time constraints.
- Accessibility, which is the degree to which MI is easily and quickly retrievable by authorized users. Low accessibility can reflect technology system incompatibility, poor user knowledge, or poor information presentation (e.g., proper visualization enables users to gain better insights and understanding of information or to identify relevant details). This criterion is also affected by the cost for accessing MI, expressed as either monetary and/or nonmonetary terms (e.g., energy consumption). Observe that accessibility directly impacts on the level of system adoption and user acceptance. Indeed, if access to information is not easy, the user may ignore it.
- Immediate usability, defined as the degree to which MI can be used directly to support IEDM activity, without a need of organizing or processing it.

Unlike syntactic and semantic layers, pragmatic quality cannot usually be objectively assessed. Indeed, user-subjective and user-based judgments are normally required since pragmatic quality is strictly related to the user's information needs. All syntactic, semantic, and pragmatic criteria of the QoMI framework contribute to the overall, metacriterion of validity of MI for a specific IEDM problem

C. Factors Related to Information Producers and Information Users

It is well known that product quality strongly depends on both production process and organization quality levels [43]. Thus, QoMI issues should consider not only measurement results but also the features of both the measurement process (i.e., the set of all activities performed from empirical property sensing to measurement result delivering) and the organization responsible for that process. The quality of the measurement process depends on the adopted method and procedure, the performance of employed instrumentation and, for not fully automated processes, the qualification of operators. Regarding the organization, qualification and reputation are relevant factors. Qualification derives not only from certification but also from past satisfactory interactions with the user and generally depends on the kind of measurement (e.g., qualification concerned with temperature, pressure and humidity measurements does not guarantee that the organization is qualified to measure air-pollutant concentrations). Conversely, reputation refers to a publicly held opinion about the organization's competence and trustfulness.

Regarding the impact of MI on decision confidence, it depends not only on quality but also on how the MI is used. When human decision-makers are involved, relevant factors are as follow.

- *Experience Level:* If the user is familiar with the received information, her experience facilitates the detection of possible errors; conversely, she could rely too much on experience, so paying less attention to unexpected information.
- *Time Constraints:* Time pressure can promote the adoption of simplifying heuristics, which can cause decision flaws.
- *Information Overload:* In the presence of a large amount of information, the user might process it superficially or process only parts of it, especially if there are time constraints; a proper balance between available processing time and information amount mitigates the risk of wrong conclusions.

D. Application of the Framework

The proposed framework supports the operational definition of QoMI for a specific IEDM activity, even if it does not provide a complete set of QoMI-related criteria. To better clarify this concept, once the properties considered relevant for a given IEDM problem have been identified, consider that assessment of QoMI requires performing the three following subsequent steps.

- *Quality Identification:* In this step, criteria recognized useful for a given IEDM problem are selected; then each

selected criterion is specified by identifying one or more appropriate characteristics and the related indicators (e.g., the criterion of object and measurand identification can be evaluated by some components of measurement uncertainty, which can be quantified as standard deviations); also, the range of acceptable indicator values is derived
- *Quality-Related Indicator Evaluation:* During this step, each identified indicator is evaluated, but no judgment is expressed about the obtained values
- *Quality Assessment:* For each indicator, the obtained value is compared with the corresponding range of acceptable values; a judgment is then applied to establish its level of quality and possible quality deficiencies, and improvements are also identified

The proposed framework can be advantageously applied during the design stage of an information gathering system as well as for checking *a posteriori* possible design deficiencies. In this respect, some criteria listed above can be unimportant for a specific IEDM problem, while others, not included in Table I, could be of crucial importance.

Moreover, not all criteria have necessarily the same importance. If, for example, IEDM is related to long-term planning, then ensuring low measurement uncertainty is not a primary issue, given that decisions will be strongly affected by uncertain forecasts. Conversely, short-term planning decisions with potentially severe consequences often require low measurement uncertainty.

E. Information Updating

The whole pragmatic information about the measurands used to support IEDM exhibits two components as follows.

- *a priori* information, which is related to the (explicit or tacit) knowledge already owned by the user about the context of MI and its relevance for the specific IEDM at stake. This information is retrieved from the user knowledge base by exploiting the syntactic and semantic information, possibly through processing or performing auxiliary measurements.
- *a posteriori* information, which represents the user understanding of the meaning of MI.

Representing the syntactic, semantic, and *a priori* information about the measurands x as $s(x)$, $m(x)$, and $p(x)$, respectively, the *a posteriori* pragmatic information $p^*(x)$ can be obtained by mapping the triple $(s(x),\ m(x),\ p(x))$ into the pragmatic space through an abstraction process based on the user knowledge as shown in Fig. 4, that is

$$p^*(x) = k(s(x), m(x), p(x))$$

where $k(\cdot)$ is the so-called knowledge function [31]. By changing $k(\cdot)$ or *a priori* information $p(x)$, the same syntactic information $s(x)$ can be interpreted in a different way. Also, to ensure that data are univocally interpreted, the knowledge function and *a priori* pragmatic information have to be predetermined, as required by the intersubjectivity criterion. Conversely, if the knowledge function and/or *a priori* information are fuzzy, also data interpretation is fuzzy.

Finally, quality assessment can be carried out in different ways and stages, depending on the coupling between MI and IEDM. For example, in the case of intentionally designed information sources, some criteria (e.g., domain integrity, domain and time consistencies, specificity, and timelines) would be assessed at acquisition time, whereas other criteria could be assessed at design time. The prioritization of criteria and the scheduling of their assessment are among the several possible extensions of the presented version of the framework.

F. Operationalization of the Framework

The conceptual structure presented so far is operationalized as a procedure including two main stages: a top-down analysis and a bottom-up synthesis, as shown in the flowchart in Fig. 5, which also highlights that the synthesis, being strongly dependent on the domain of the QoMI process, cannot be further detailed in a general-purpose framework. In fact, the evaluation of QoMI is a knowledge intensive endeavor, not a routine task: this procedure, including Table II containing the key evaluation factors of criteria identified as meaningful and sketched in the application example below, should be considered only as a blueprint that supports the elicitation of expert knowledge. In this perspective, the information formalized in the procedure should be acknowledged as always revisable, through feedback loops (which are not explicitly included in the flowchart in Fig. 5 for keeping it simple).

VI. Application Example: The Air Quality Index

We sketch here an example of the application of the framework, related to the measurement of pollutants in the air. According to [44], 92% of the world's population lives in places where air quality levels exceed the World Health Organization (WHO) limits. Since human health conditions and the environment are affected by air quality, nations, governments and decision makers are interested parties in the overall discussion on how to improve it. Accordingly, several IEDM processes are based on the evaluation of an air quality index (AQI), as it is for example the case of a city manager in charge of deciding whether traffic in an urban area should be stopped, in response to a concentration of pollutants exceeding a set threshold. To this purpose, several pollutants monitoring stations (PMSs) are dislocated in the considered city area, thus forming a measurement station network (MSN) that collects and transfers MI to a data collector. Each PMS measures various kinds of physical quantities, such as concentrations of PM2.5, PM10, SO_2, CO, and NO_2. However, not all PMS measure the same set of quantities and update MI with the same frequency. The measured values are then processed and aggregated to produce an AQI [44]. For instance, the value of concentration of each pollutant is normalized in the range (0, 500), and then, the obtained values are aggregated by means of a weighed mean or the min-max operators [44]; in the latter case, the largest normalized value is taken as the AQI value. Usually, values resulting larger than 100 correspond to violations of regulations and suitable decisions should be made by the city administrators [44]. Several applications of the AQI other than traffic-related decisions can be envisioned,

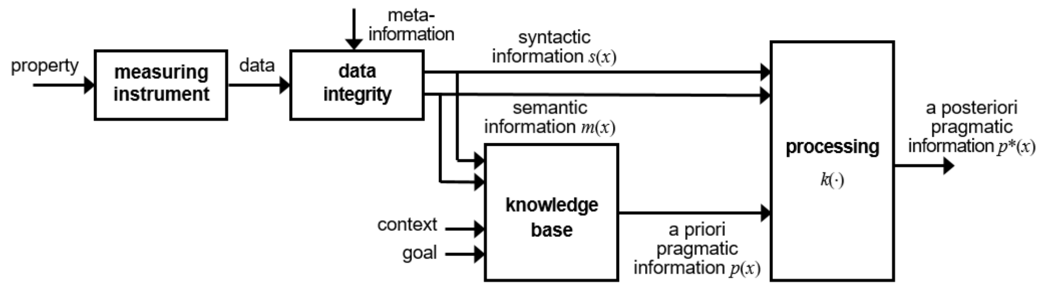

Fig. 4. Model of the different aspects of MI and *a posteriori* pragmatic information generation.

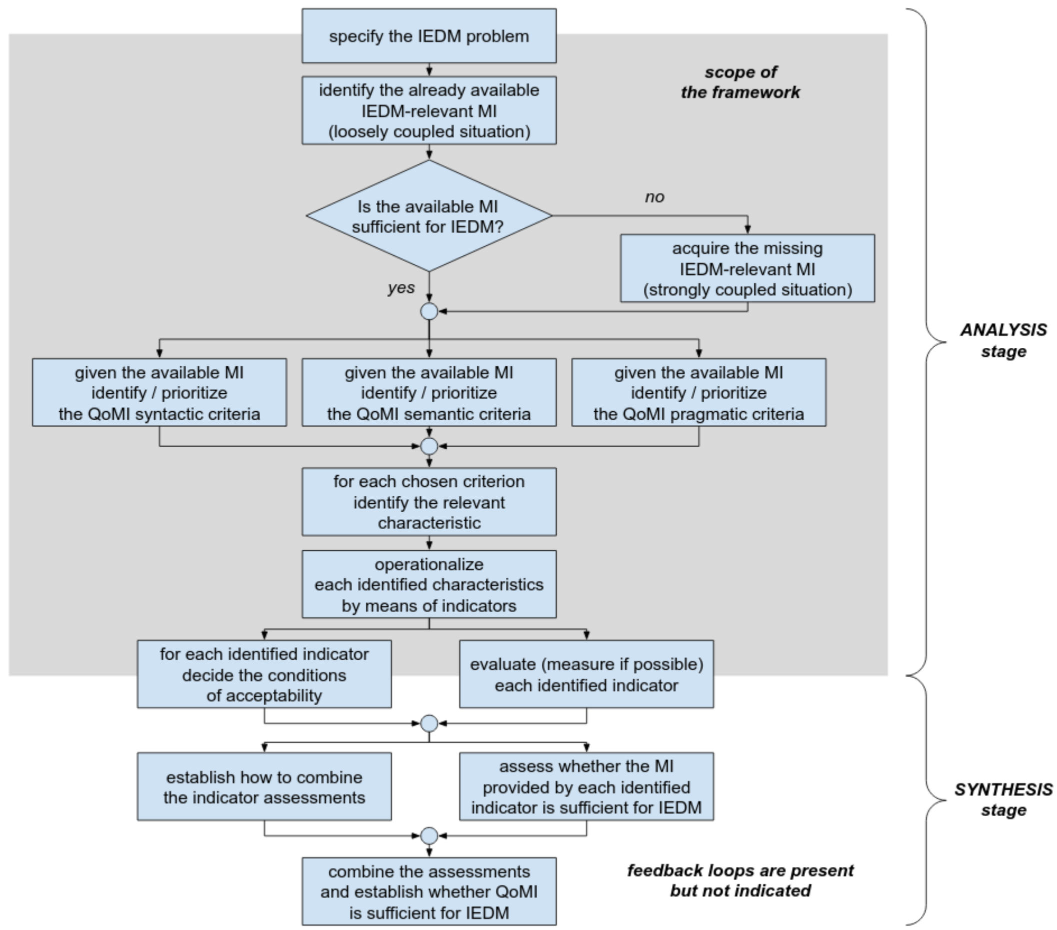

Fig. 5. Procedural presentation of the framework.

such as allocation of resources, ranking of locations, or public information [44].

In such a complex scenario, MI returned by MSNs is an important asset, and the validity of the results of IEDM processes critically depends on the related quality. Hence, the proposed framework can be usefully exploited as a tool to elicit and validate technical choices about the QoMI; it enables a disciplined analysis of many relevant issues involved in the problem, possibly including weaknesses and strengths of the measurement infrastructure. The framework is customized by identifying the most relevant criteria in the context and for each of them the corresponding characteristics and indicators. Thus, its application can result in the production of checklists, rules, and guidelines, as outcomes of reasoning aimed at planning or revising the process handling MI for decisionmaking purposes.

For instantiating the procedure described in the flowchart in Fig. 5 in reference to a specific application of the framework, an approach based on key evaluation factors can be adopted for each criterion identified as meaningful.

- What needs are satisfied?—provides the reason for the relevance of the criterion.
- Characteristics and indicators—lists relevant characteristics and indicators.
- How can the requirement be trustworthy evaluated?—specifies available tools and knowledge production

TABLE II
KEY EVALUATION FACTORS OF CRITERIA IDENTIFIED AS MEANINGFUL FOR THE AQI EXAMPLE

	What needs are satisfied?	**Characteristics and indicators**	**How can the requirement be trustworthy evaluated?**	**What if the evaluation fails?**	**Notes**
Syntactic quality					
Domain integrity	Do values belong to the corresponding scales of instrument indications?	Binary indicators about belonging to the scales.	Objective software-based procedures can be employed for evaluation.	Identify the causes of lack of integrity and remove their effect on MI.	These values might be identified as outliers in the available sample, possibly resulting from a data communication error, or a faulty sensor.
Indication scale resolution	Is indication scale resolution of PMSs adequate to support decision making?	Technical specifications about indication scale resolution of PMSs.	Check the technical specifications of used PMSs.	Perform technical improvements to increase poor indication scale resolution of PMSs.	
Semantic quality					
Object identification	Has been sensors correctly deployed so that they provide MI about air quality in the desired location?	Coordinates of the sensor locations.	Compare sensor location measurement with specified coordinate values.	Perform technical intervention to ensure correct sensor location.	
Measurand identification	Are the employed PMSs sufficiently insensitive to properties other than the measurand?	Sensors and PMSs sensitivities to influence quantities as provided by technical specifications or experimentally determined.	Compare measured sensitivities with thresholds defined in PMS design.	New sensors or PMSs must be procured. Alternatively, corrections can be applied if related models are available.	This relates to sensitivities to influence quantities such as gases or environmental conditions.
Intersubjectivity	Do sensors and subsequent processing activities provide unambiguous information?	PMS calibration diagrams.	Onsite metrological confirmation may reveal insufficient intersubjectivity.	Identify the causes of lack of intersubjectivity and reduce their effect on MI. Recalibrate PMSs.	
Measurement scale resolution	Does MI exhibit adequate resolution to support decision making?	Specifications about resolution for any PMSs.	Check the technical specifications of used PMSs.	Perform technical improvements to increase poor PMS resolution.	Many air quality applications require capability to measure CO_2 concentrations with a resolution of 5 ppm [46].
Context-awareness	Is the provided MI properly contextualized?	Empirical environment properties established by design or applicable laws and regulations.	Check the validity of the adopted measurement context model.	Improve the adopted measurement context model.	Identification of influence quantities including competence of operators, supporting documentation and procedures.
Domain consistency	Does MI conform fundamental requirements about admissible or expected values?	Ranges of admissible or expected values.	Compare measured values with specified ranges.	Identify the causes of inconsistency and reduce their effect on MI.	Extremely large values of CO_2 when the context implies the contrary (windy day with low traffic volumes). High correlation is expected between CO_2 and PM concentrations [47].
Time consistency	Is measurement repeatability confirmed?	Time stability of provided MI.	Check stability of replicated measurements obtained over a short period of time by using a given procedure, same operators, same PMSs, same operating conditions, in the same location.	Perform technical improvements of PMSs to increase poor time consistency.	This might be related to PMS affected by relevant unexpected wideband noise.
Conciseness	Is the provided MI free of content useless to decision making?	Features of MI established by design.	Audit and review of PMS output.	Detect and eliminate useless MI content.	MI provided with too many digits. MI about properties that is useless for decision making.

TABLE II

(Continued.) KEY EVALUATION FACTORS OF CRITERIA IDENTIFIED AS MEANINGFUL FOR THE AQI EXAMPLE

Pragmatic quality					
Specificity	Is measurement uncertainty less than target uncertainty?	Target uncertainty for MI produced by each sensor and PMS.	Perform on site calibration.	Perform technical improvements to increase measurement specificity.	
Sufficiency	Is MI sufficient to support IEDM?	List of measured quantities.	Check if the measured quantities suffice to fulfill IEDM requirements.	Additional sensors or PMS must be deployed.	Lack of information about one or more quantities needed to determine AQI in a given location.
Confidentiality	Is MI available only to authorized users?	Different access levels to MI.	Capability to guarantee the access to MI only to authorized people.	Authorities might need to be informed if possible societal impact may occur.	
Timeliness	Is MI available within a specified timeframe?	MSN time-to-information retrieval.	Compare actual MSN time-to-information retrieval with the specified timeframe.	Perform technical improvements to reduce MSN time-to-information retrieval.	Sensor response time to sudden changes can be too long to ensure adequate to support decision making.
Immediate usability	Is MI immediately usable to support decision making?	Level of usability subjectively evaluated by MI users.	A survey involving MI users.	Implement suitable sensor data processing and improve user's interface.	Sensor data undergoes suitable processing that can include also decision procedures aimed at increasing MI usability.

mechanisms to provide decision makers with sufficient information to decide about the criterion satisfaction.
- What if the evaluation fails?—lists the actions to be taken when the evaluation of the criterion is negative.

Filling on this table is itself an activity that enriches the MI user awareness about the properties of the specific decision problem and a knowledge management tool allowing knowledge elicitation and sharing among interested parties. Finally, it may inform about possible missing or redundant activities in the production and analysis of MI for the specific application.

VII. DISCUSSION

As stated in Section I, papers specifically dealing with QoMI are virtually lacking in the literature. Thus, discussion about differences and novelties proposed in this article with respect to the existing literature will be focused on papers concerned with QoI in sensor networks or IoT in their parts involved with measurement. To that aim, the different perspectives listed in the following are considered.

- *Quality Dimensions, Criteria, and Characteristics:* Most papers published in the literature call "dimensions" the different aspects along which judgments about the "fitness for use" of information are carried out. Conversely, the proposed framework shows that it is often advantageous adopting a more structured approach by distinguishing three levels of entities, criteria, characteristics, and indicators, in turn classified in the semiotic layers.
- *Categorization:* In the literature, a plethora of QoI dimensions have been proposed, which are organized in reasonable, but *ad hoc* defined, broad categories. For example, some papers categorize QoI dimensions in three main classes, called "intrinsic," "external," and "context" [22], 43], [48], while others consider additional classes (e.g., accessibility, representational, and so on) [10], [49]. Conversely, we think that the adoption of a semiotic approach provides a well-defined, powerful, and general-purpose categorization. The validity of that approach is also recognized by the ISO 8000 family of standards [9], [29], which proposes a categorization based on semiotic layers, but dealing with the general topic of QoI without considering the peculiar characteristics of QoMI.
- *Relationship Between Semiotic Layers of MI:* To the best of the authors' knowledge, only very few papers tackle the relationship between the three information semiotic layers [23]. Considering the relevance of the topic, in this article, a model that links *a posteriori* pragmatic information with the syntactic, semantic, and *a priori* pragmatic information has been proposed in Section V-E (see Fig. 4).
- *Relationship With the Real World:* Information characteristics related to the empirical world are usually of highest interest when QoI in sensor networks or IoT is of concern. In particular, trustworthiness is probably the most investigated QoI characteristic, even if it is generically named accuracy in the literature [43], [48]. Indeed, information returned by sensors and IoT devices is often noisy, biased, and incomplete due to sensor and transmission inaccuracies, possible power failures, or wrong operating conditions. Some work refers also to the concept of consistency, but it has an author-dependent meaning [3], [50]. The need for information about measurement context is discussed only in a few documents [3], [39], [48].

The proposed framework emphasizes the relationship between MI and the empirical world by assigning to it one of the three semiotic layers: semantics. Moreover, whenever possible, the related characteristics are not defined *ad hoc*, but they refer to official documents (such as [34]) and the literature in the field of instrumentation and measurement [1], [40], [51].

- *Objective and Subjective Aspects of Quality:* While many QoI frameworks proposed in the literature are concerned with both subjective and objective quality dimensions [43], frameworks dealing with sensor networks and IoT are focused on objectivity [3], [10], [13], [48], 49]. The same occurs in the proposed framework. However, this article highlights that only syntactic quality assessment is a completely objective process, whereas semantic quality assessment involves some degree of subjectivity in which modeling of both the considered object and the measurement context depends on measurement purpose. Conversely, pragmatic quality assessment exhibits strong subjective components.
- *Information System Performance:* Various published papers concerned with sensor networks or IoT are focused on the impact on QoI of the information system performance related to acquisition, transmission, and visualization [48], [50]. Conversely, although recognizing that QoMI strongly depends on both the measurement system and the measurement process, this article focuses on the identification of general-purpose criteria characterizing QoMI.

VIII. Framework Limitations and Future Research Directions

The aim of the proposed framework is to provide a contribution to identification, assessment, communication, and improvement of QoMI. However, in pursuing this goal, the framework has also some limitations that could be addressed in future research.

First, an exhaustive analysis of QoMI should consider that there can exist interdependencies between quality criteria (e.g., lack of domain integrity due to missing values can affect sufficiency or strict requirements on timeliness can affect measurement uncertainty). Explicit recognition of interdependencies is crucial since they may affect quality assessment results and may have implications on the selection of assessment methods. Despite interdependencies that are often strictly related to the specific IEDM problem, we expect that some general guidelines to identify them and assess their impact on QoMI can be developed.

A second limitation of the framework is that it considers only objective characteristics. Indeed, even information rated highly in terms of all considered quality criteria may still be deficient with respect to some specific user's needs. However, a further pragmatic characteristic—it could be called "measurement value"—that considers a comprehensive user perception of QoMI could be usefully added to the framework, in order to assess the validity of the adopted quality criteria and to confirm that no useless redundant criteria are included, nor relevant quality aspects are neglected.

A third direction for framework development can be the definition of guidelines to determine the impact of adopted instrumentation performance on QoMI. This work could be grounded on the existing literature on the topic, such as [36], [39], [40], [51], and [52].

A last direction of research could consider the identification of the sources of uncertainties raising in an IEDM process, when considering all process steps, from decision planning, to information gathering, decision-making, and decision implementation. A preliminary study on this topic can be found in [1].

IX. Conclusion

When dealing with data-driven decision making, QoMI represents a critical factor. In fact, inadequate quality can result in wrong decisions with unexpected and unintended, potentially severe, consequences. To address this issue, a general-purpose framework has been proposed in this article. It offers a metamodel that can guide researchers and practitioners in acquiring awareness when dealing with decisions based on MI, so facilitating the definition, assessment, communication, and improvement of the elusive concept of information quality.

The framework acknowledges that measurement uncertainty is crucially important because strictly related to decision confidence but also emphasizes that it does not suffice to guarantee MI quality. Consequently, the framework includes a structured set of general-purpose criteria, organized according to the syntactic, semantic, and pragmatic layers of semiotics. Each criterion is described in terms of one or more characteristics, each one defined by means of one or more indicators, whose ranges of acceptable values are derived from decision-making requirements. The framework can be tailored to specific situations by neglecting general-purpose criteria that do not fit with the considered situation or adding new criteria believed relevant.

An example of application has been presented to enable a deeper understanding of the framework, so clarifying its advantages and limitations: the discussions about research quality assessment and quality of IoT-based MI show that the framework can provide a basis for the definition of common concepts and terms and for gaining awareness of strengths and weaknesses of decisions based on MI.

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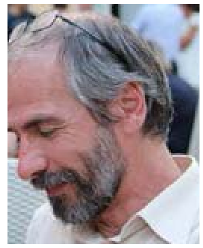

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