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Abstract

Advances in information and communication technologies, such as Radio Frequency Identification (RFID), mobile and wireless mesh networks, bring us closer to the vision of "Internet of Things", a global network of people, products or objects that can be easily readable, recognizable, locatable, and manageable over the world wide web. Such a network can provide ubiquitous and real-time information on movements of objects; and object tracking systems monitor the moving objects and register their on-going location in the context of higher-level applications, such as supply chain management, food traceability and retail, where monitoring of objects is required. This paper investigates information quality of object tracking systems and proposes an analytical model that measures the degree of information completeness of object tracking systems based on the scope and depth of their data capturing capabilities. We demonstrate that the information completeness of object tracking systems is influenced by the configuration of object tracking systems. The model may be used for both ex-ante and ex-post evaluations of object tracking systems, under the auspices of their information quality requirements, considering that their use is expected to blossom in the "Internet-of-Things" era.

Keywords: Information Quality Assessment, Object Tracking, Mathematical Modeling

1. INTRODUCTION

Advances in information and communication technologies, in the form of Radio Frequency Identification (RFID), mobile and wireless mesh networks, and smart sensors have spawned new possibilities for companies to streamline their information requirements. Indeed, visionaries have seized on the concept of "Internet-of-Things" to define a network of objects that can be easily readable, recognizable, locatable, and manageable over the world wide web. Such a network provides companies with unprecedented benefits, which are predominately associated with improved visibility of their internal and external supply chains.

Achieving end-to-end supply chain visibility requires companies to devise methods that monitor the quantities, current location, and life-cycle of products that are procured, produced, and sold. Hence, researchers and practitioners have proposed the notion of *object tracking systems*, as a means to effectively spot the products' paths within the supply chain. Such systems provide support to critical supply chain management processes, such as inventory management, production planning, and promotions management; and influence managers' decisions and strategy formulation on the aforementioned processes. Arguably, the effectiveness of these decisions will be directly associated with the quality of information that the decision maker has access to; namely the output information of the object tracking system. Based on the above, researchers have recently started to investigate *information quality* on object tracking systems (Thiesse & Fleisch 2008, Kelepouris & McFarlane 2008).

This article proposes an analytical approach, based on Graph theory, to model and assess objectively the information completeness of object tracking systems. First, we model the object tracking systems in regard to their data tracking scope and depth. Then, we demonstrate that the information completeness of object tracking systems is influenced by the scope and depth of their tracking capabilities. The model may be used for both ex-ante and ex-post evaluations of object tracking systems, under the auspices of their information quality requirements, considering that their use is expected to blossom in the "Internet-of-Things" era.

We structure the paper as follows: initially we present a short overview on the existing research efforts on information quality, both generally and under the prism of this research. Next, we provide an in-depth presentation of the proposed model and its mathematical grounding. The paper concludes with a discussion of the academic and managerial implications of our work and the identification of avenues for further research.

2. RELATED WORK

The term 'information quality' (IQ) has coined a stream of research that investigates alternative ways to measure the "fitness-for-use" (Wang & Strong 1996) of information in a particular IS context. Over the past years, studies have reached to the consensus that information quality is an indirect predictor of IS success, leading to increased levels of user satisfaction and ease of use (DeLone and McLean, 1992, 2003, 2004, Wang 2008).

Research on information quality follows a dichotomy in its investigation lenses. On the one hand, scholars attempt to generate classification frameworks in order to capture the elements that define quality in a given system. Because information quality is a multi-dimensional concept (Ballou & Pazer 1995, Wang & Strong 1996**,** Lee et al. 2002, Batini et al. 2009), research efforts in this sub-stream have emphasized on the identification of quality indicators in order to develop different quality assessment frameworks. In this spirit, the information quality literature provides alternative classification frameworks of information quality dimensions (Wand & Wang 1996, Wang & Strong 1996, English 1999, Bovee 2003, Naumann 2002). However, there are numerous discrepancies in the definition of most dimensions due to the contextual nature of quality (Batini et al. 2009). In effect, these classifications define a basic set of information quality dimensions, including accuracy, completeness, consistency, and timeliness, which comprise the common denominators on the classification efforts for the majority of scholars (Pipino et al. 2005).

The second sub-stream of research on information quality refers to the development of methods and tools to assess information quality in information systems. Results in this area may be classified in two broad categories depending on the epistemology and philosophical stance of researchers. The first category refers to the formulation of holistic assessment methodologies that propose quantifiable metrics for each information quality dimension. Notable examples include the AIMQ methodology which evaluates IQ based on benchmarking (Lee et al. 2002), the Data Quality Assessment (DQA) methodology which makes a distinction between subjective and objective quality metrics (Pipino et al. 2002), and the Information Quality Measurement (IQM) methodology which specifies both a quality framework defining quality criteria and an action plan prescribing how to perform quality measurements (Eppler & Helfert 2004). Batini et al. (2009) provide a systematic and comparative survey of such methodologies.

The second category refers to the specification of constructs that perceptually assess information quality in information systems and estimate its effect on performance and social factors such as usability, usefulness, risk, trust, and behavioral intention to use the system. The most common research methods for the collection of assessment data are field studies and surveys. Several models have been developed and field tested in multiple contexts such as inter-organizational data exchanges (Nicolaou & McKnight 2006), adoption of web sites (Lin & Lu 2000) and use of mobile internet among other information systems (Shin 2007).

Taking into account the above, this work aims at providing a holistic perspective in the investigation of information quality for object tracking systems. We define object tracking as the capability of a system to recognize the flow of objects within a number of capture locations and register their on-going location. Examples of object tracking systems appear on supply chain management, food traceability and retail to name but a few applications where monitoring of objects is required. In this context, information quality has gained increased importance following the emergence of Auto-ID technologies, and especially RFID, which promise to provide increased visibility of the supply chain (Sellitto et al. 2007). Hence, researchers recently started to evaluate the performance of tracking systems using, primarily, qualitative criteria, that focus on certain IQ dimensions (Sahin et al. 2002). Nevertheless, a formal method to quantitatively assess the impact of Auto-ID technologies on the IQ of a tracking system is still missing. In this work, we employ a meta-analytical viewpoint that measures the degree of IQ for an object tracking system based on its data capturing and identification capabilities. We contend that alternative configurations of an object tracking system influence its IQ. The following section presents our efforts to model the alternative configurations of object tracking systems.

3. MODELING THE ALTERNATIVE CONFIGURATIONS OF OBJECT TRACKING SYSTEMS

During the business workflow, the objects move through different locations and we aim to capture and identify these movement tracks in order to provide with updated objects' tracking information. Observing the objects flows, we identify all the individual locations the objects may occupy at every point in time. Based on the patterns governing the objects flows, we generate object flow paths.

An *object flow path* is a set of locations $\{l_1, l_2, ..., l_w, l_x\}$, such that each pair (l_i, l_j) represents the object transition from location l_i to location l_j during the business workflow; and the locations are distinct.

Further, composing the flow paths, we construct the *object flow graph*. It is a directed simple graph $G = (V, E)$ consisting of a set V of nodes together with a set E of edges, corresponding to directed connections between nodes. Each node represents a distinct location the object visits. Respectively, edges correspond to the object's transitions between locations.

The *object flow graph* is associated with the *adjacency matrix* L reporting the object transitions between locations. L is a *square* $N \times N$ *matrix* (Table 1), where N is the number of distinct locations. Each element of L, l_{ij} is binary; l_{ij} is 1, if the corresponding locations l_i and l_j are endpoints of an edge, meaning the object transits between locations l_i and l_j; else l_{ij} is 0. Also, if $i = j$, l_{ij} is 0, since there are no loops.

$$L = \begin{pmatrix} l_{11} & l_{12} & \dots & l_{1N} \\ l_{21} & l_{22} & \dots & l_{2N} \\ \dots & \dots & \dots & \dots \\ l_{N1} & l_{N2} & \dots & l_{NN} \end{pmatrix}, l_{ij} = \begin{cases} 1, & if \;\; \ni (l_i, l_j) \;\; and \;\; i \neq j \\ & 0 \end{cases}$$

Table 1. Adjacency matrix L of a N-order object flow graph

According to the above quantitative modeling of the objects flow, if we capture and identify the objects at the locations they transit between moving along the flow graph, then we can succeed in monitoring and tracking them.

Consequently, an object tracking system captures and identifies the objects at the individual locations the objects flow through, in order to provide with updated object's tracking information. The locations are transformed to *capture points* that read objects moving through or standing at the points. The objects are identified from their label that contains their identity.

Thus, we define an *Object Tracking system* to be a *network* of *capture points* that read and identify *labeled* objects.

Certainly, we could utilize *AIDC-Automatic Identification and (Automatic) Data Capture* technologies to automate the capturing and identification of objects movements. AIDC or Auto-ID technologies share the capabilities of *automatically identifying and capturing objects*, resources and persons; and communicating tracking information about them into computer systems. Barcodes, RFID (Radio Frequency Identification), biometrics, magnetic stripes, optical character recognition (OCR), smart cards and voice recognition are under the umbrella of these technologies. Then, an AIDC-enabled object tracking system would be a network of capture points equipped with AIDC-readers that capture and identify AIDC-labeled objects, such as a set of RFID readers that scan RFID-tagged objects. However, our research findings below are applied on object tracking systems whether or not we employ Auto-ID or any other future capturing and identification technologies.

To continue, *an Object Tracking system* collects a stream of captured object movement tracks of the form (*object_identity*, *timestamp*, capture point_*identity*) reporting when a labeled object associated with this identity was scanned at a capture point associated with this identity. The capture point's identity refers to its location. For example, when we employ barcode scanners to track the objects, the object_identity is the barcode that characterizes only the object class, e.g. if a product item is a shampoo or a soda. On the contrary, RFID-readers provide with unique object_identity, meaning which soda can was scanned; requiring neither human involvement, nor line-of- sight to capture the RFID-tagged objects.

Then, the data stream of object movement tracks is filtered, cleaned and aggregated per object_identity to offer with identification and tracking information about the flow of objects during the workflow.

Extracting the objects' potential locations from the object flow graph, we infer all the potential points where we can capture objects. But, at the capture points we read only labeled objects. Consequently, to configure the object tracking system we need to answer a two-fold question: *where* the system captures objects and *what object level*s we will label to track them. For example, a RFID-reader on a retail store's shelf scans products labeled at item-level; or, at the back-room entrance staff scans the products labeled at case-level and pallet-level to verify the shipments. Therefore, alternative configurations of object tracking systems are offered depending on the values of two configuration variables: the *location of capture points* and the *labeling level*.

For each configuration solution, the value of the variable *location of capture points* is assosiated with a *column vector* CP reporting the locations l_i where we capture labeled objects. Each element of CP, cp_{i1} is binary; cp_{i1} is 1, if the corresponding location l_i is a capture point; else, cp_{i1} is 0. Considering objects transit between N individual locations l_i reported in matrix L, CP is a $N \times 1$ column vector and each configuration includes $\sum_{1}^{N} cp_{i1} \leq N$ number of capture points.

Respectively, the variable *labeling level* is related with the *object levels* that represent the hierarchical relationship among objects. We refer individually to each object level with an element from the set $\{1, \ 2, \ \ldots \ ,K\}$ consisting of the object levels, where the top level is K. A 1st-level object is at the bottom of object hierarchy and contains no objects. Traversing the hierarchy to the way down, each j^{th}-level object may be a parent object containing $(j-1)^{th}$-level objects. For example, in the retail industry, a pallet (top-level) is loaded with cases (2nd-level) and a case is loaded with items (1st-level).

Therefore, the value of the variable labeling level is associated with a row vector LL reporting the object levels we label in order to capture them. Each element of LL, ll_{1j} is binary; ll_{1j} is 1, if the corresponding j^{th}-level objects will be labeled; else, ll_{1j} is 0. Considering, we have K distinct object levels, LL is a $1 \times K$ row vector and each configuration captures $\sum_{1}^{K} ll_{1j} \leq K$ distinct object levels.

Ultimately, the alternative configurations of object tracking systems are expressed as function of the two variables. Specifically, each configuration solution is associated with their product $C = CP \times LL$. The *configuration matrix* C reports which object levels the system tracks at which locations. C is a $(N \times 1) \times (1 \times K) = N \times K$ *matrix*, where each element $c_{ij} = cp_{i1} \times ll_{1j}$ is binary; c_{ij} is 1, if the system tracks labeled ll_{1j}^{th}-level objects at location cp_{i1} ; else c_{ij} is 0.

The alternative values of the variable capture points location CP equals 2^N. Respectively, the alternative values of the variable labeling level LL equals 2^K. Thus, the total number of alternative configurations of object tracking systems equals the product $2^N \times 2^K$.

Tables 2 & 3, below, summarize the properties of the system configuration variables and the configuration solutions, respectively. At the next section, we model the information completeness of object tracking systems based on the mathematical model of the system configuration; and demonstrate that completeness depends on the system configuration.

To exemplify the formal model of object tracking systems configurations, we consider products that flow into a retail store when shelf replenishment takes place. Products flow on the path (backroom, backroom exit to sales floor, shelf). We could install a product tracking system that employs RFID readers at the shelves (i.e. capture points) to monitor the products at item-level. But, an alternative system configuration would utilize an RFID reader at the backroom exit to sales floor to monitor the products at case and item level; and would capture the products' purchases at the POS sales. Both configurations of the product tracking system can provide with the available products' stock on the shelves.

	Configuration Variables	
	location of capture points	labeling level
Annotation	$N \times 1$ column vector CP	$1 \times K$ row vector LL
Values & Properties	$CP = \begin{pmatrix} cp_{11} \\ cp_{21} \\ \dots \\ cp_{N1} \end{pmatrix}$	$LL = \begin{pmatrix} ll_{11} & ll_{12} & \dots & ll_{1K} \end{pmatrix}$
	cp_{i1} is binary	ll_{1j} is binary
	$cp_{i1} = 1$, if location l_i is a capture point	$ll_{1j} = 1$, if j^{th}-level objects are labeled
	2^N alternative values of CP	2^K alternative values of LL
	$\sum_1^N cp_{i1} \le N$	$\sum_1^K ll_{1j} \le K$

Table 2. Configuration Variables of Object Tracking systems

	Configuration Solution
	$C = CP \times LL$
Annotation	$(N \times 1) \times (1 \times K) = N \times K$ matrix C
Values & Properties	$C = CP \times LL \Rightarrow C = \begin{pmatrix} cp_{11} \\ cp_{21} \\ \dots \\ cp_{N1} \end{pmatrix} \times \begin{pmatrix} ll_{11} & ll_{12} & \dots & ll_{1K} \end{pmatrix} \Rightarrow$
	$C = \begin{pmatrix} (cp_{11} \times ll_{11}) & (cp_{11} \times ll_{12}) & \dots & (cp_{11} \times ll_{1K}) \\ (cp_{21} \times ll_{11}) & (cp_{21} \times ll_{12}) & \dots & (cp_{21} \times ll_{1K}) \\ \dots & \dots & \dots & \dots \\ (cp_{N1} \times ll_{11}) & (cp_{N1} \times ll_{12}) & \dots & (cp_{N1} \times ll_{1K}) \end{pmatrix}$
	$c_{ij} = (cp_i \times ll_j)$ is binary
	$c_{ij} = 1$, if the system tracks labeled ll_{1j}^{th}-level objects at location cp_{i1}
	$2^N \times 2^K$ alternative configurations C

Table 3. Alternative Configuration Solutions of Object Tracking systems

4. MODELING THE INFORMATION COMPLETENESS OF OBJECT TRACKING SYSTEMS

An object tracking system is a network of capture points that monitor labeled objects at the locations they move between traversing their flow paths. We collect from the set of capture points a data stream of object movement tracks of the form (object_identity, timestamp, capture point_location) that report objects moving through or standing at the points on flow paths.

To model the information quality of captured movement tracks of objects flowing along their paths, we assume there are no erroneous readings and no time delay is introduced between the real flow and the capturing. Hence, *a stream of object movement tuples, aggregated from the capture points located on a path, is accurate and timely* in the sense that each object movement tuple carries error-free, up-to-date object tracking information.

Still, with respect to scholars [e.g. (Ballou & Pazer 2003, Shankaranarayanan & Cai 2006)], who commonly define completeness, context-independently, to be "the ratio of the values that are recorded to the values that could have been reported", we adopt this "absolute standard for completeness that serves as a benchmark (Shankaranarayanan & Cai 2006)" and adjust it to devise the following definition:

The *completeness of a stream of object movement tuples, aggregated from the capture points located on a path,* is the *ratio* of the object movement tuples (object_identity, timestamp, capture point_location) that are captured to the tuples that could have been captured if all locations on the path were capture points and all object levels that flow on the path were labeled in order for all object instances to be captured. It takes a measure between 1 (perfectly complete) and 0 (most incomplete).

Thus, *a stream of captured object movement tuples, collected from an object tracking system on a path, is complete* only if have captured every object moving through or standing at all path locations. In this spirit, a complete stream of captured object movement tracks from a path requires an object tracking system that sets capture points at each location of the path; and applies labels on each object level that moves along the path in order to read and identify all object instances. Consequently, *the completeness of an object tracking system per object flow path depends on the system configuration variables, location of capture points and labeling level.*

To continue, we model quantitatively the completeness PC of an object tracking system per object flow path (Table 4), based on the next assumption to simplify the formulas. Either a product moves through or stands at a capture point, still one movement tuple is captured. For example, when a shelf in a retail store is a capture point, we consider the tuples generated for each product instance to be aggregated in one.

The denominator of the fraction PC reports that each object, out of po object instances, flowing between locations on the path, is labeled and captured at all locations pl of the path that all function as capture points. Thus, po object instances flowing on the path would generate $(po \times pl)$ movement tuples, provided that our object tracking system includes captures points at all locations of the path; and all object levels flowing on the path are labeled. The total number of object instances po includes each i^{th}-level object instances contained in $(i+1)^{th}$-level parent objects, where $i \ni \{1, \quad 2, \quad \ldots \quad ,K\}$ and K is the top object level.

Further, the numerator of the fraction PC reports the actual number of captured object movement tuples when po object instances traverse the path. Whenever a j^{th}-level object moves through or stands at a location l_i of the path, it is captured only if the object tracking system captures labeled j^{th}-level objects at location l_i. But, we have already modeled the ability or not of a system configuration C to track a labeled j^{th}-level object at path location l_i through the product $c_{ij} = cp_{i1} \times ll_{1j}$, where elements cp_{i1} and ll_{1j} of vectors CP and LL report the values of the system configuration variables capture points location and labeling level, respectively. Therefore, when one j^{th}-level object traverses a path $(l_1,l_2),\ldots,(l_w,l_x)$ with pl distinct locations, an object tracking system captures $\sum_{1}^{pl} cp_{i1} \times ll_{1j}$ movements, where i takes values from the set $\{1,2,\ldots,w,x\}$ of pl individual locations comprising the path. Respectively, when po object instances traverse the path, the captured movement tuples equal $\sum_{1}^{po}\sum_{1}^{pl} cp_{i1} \times ll_{1j}$, where i takes values from the set $\{1,2,...,w,x\}$ of pl individual locations comprising the path; and each object instance has its own j-level.

Ultimately, the mathematical modeling confirms that *the completeness of an object tracking system, per object flow path, depends on the system configuration variables, location of capture points and labeling level*. Table 4, below, includes the analytical expression of the completeness of an object tracking system configuration solution, per object flow path.

<table>
<tr><th colspan="2">Completeness of Object Tracking Systems' Configurations, per object flow path</th></tr>
<tr><td colspan="2">po: # object instances traversing the path, $po \geq 1$</td></tr>
<tr><td colspan="2">path $(l_1,l_2),...,(l_w,l_x)$ with pl distinct locations</td></tr>
<tr><td colspan="2">$pl \leq N$, N: # distinct locations of object flow graph</td></tr>
<tr><td colspan="2">$$PC = \frac{\sum(object\_identity,\ \ timestamp,\ \ capture\ \ point\_location)}{\sum_{1}^{po}\sum_{1}^{pl}(object\_identity,\ \ timestamp,\ \ capture\ \ point\_location)} \Rightarrow$$</td></tr>
<tr><td colspan="2">$$PC = \frac{\sum(object\_identity,\ \ timestamp,\ \ capture\ \ point\_location)}{po \times \sum_{1}^{pl}(object\_identity,\ \ timestamp,\ \ capture\ \ point\_location)} \Rightarrow$$</td></tr>
<tr><td colspan="2">$$PC = \frac{\sum(object\_identity,\ \ timestamp,\ \ capture\ \ point\_location)}{po \times pl}$$</td></tr>
<tr><td rowspan="2">$$PC = \frac{\sum_{1}^{pl} cp_{i1} \times ll_{1j}}{pl}$$</td><td>one j^{th}-level object instance traverses the path ($po = 1$)</td></tr>
<tr><td>i takes values from the set $\{1,2,...,w,x\}$ of pl individual locations comprising the path</td></tr>
<tr><td rowspan="3">$$PC = \frac{\sum_{1}^{po}\sum_{1}^{pl} cp_{i1} \times ll_{1j}}{po \times pl}$$</td><td>$po > 1$ object instances traverse the path</td></tr>
<tr><td>each object instance has its own j-level</td></tr>
<tr><td>i takes values from the set $\{1,2,...,w,x\}$ of pl individual locations comprising the path</td></tr>
</table>

Table 4. Completeness of Object Tracking Systems' Configurations, per object flow path

5. DISCUSSION AND CONCLUSIONS

This article presented an initial approach for the modeling of information quality of object tracking systems as a whole (i.e. a network of capture locations). The model employs a formal notation based on graph theory to map the locations and transition states of individual objects within a given network of capture locations. The outcome of the model demonstrates that information completeness is influenced by the breadth/ scope of the network of capture locations and the system's ability to monitor each object level (i.e. the tracking depth).

The advent of Auto-ID technologies has spawned a new design challenge for dynamic networks (such as supply chains) in which designers are required to identify prospective capture points for placing the data capturing artifacts (e.g. RFID readers), then evaluate their importance and contribution on the consolidation of tracking information; and, finally, assess their performance with respect to the estimated investment costs. In this context, object tracking systems usually perform two major operations; they continuously monitor product quantities on each location and they inform about possible out-of-stock events. We argue that *high degrees of information completeness of object tracking systems may lead to more accurate, complete, and, possibly, timely product tracking information* and vice versa. The proposed work bridges the gap in the field of IQ assessment of these Auto-ID enabled dynamic networks, by proposing a toolkit that supports decision making.

We consider that our research has both theoretical and practical contribution. First, opposed to the majority of IQ assessment studies, we adopt an *analytical* (*operations research*) *approach* for the evaluation of information quality. Indeed, a recent study on information quality assessment revealed that scholars evaluate information quality on information systems either through simulation, qualitative methods (e.g. case studies), or survey research (Lima et al. 2006). Our work provides a first step towards the formulation of a systematic and formal method that objectively measures the information quality of a tracking system based on the scope of its data capturing and identification capabilities.

Furthermore, our work compliments the existing research on information quality assessment by *proposing a generic holistic model that does not focus on a particular information quality dimension*. Most information quality literature is saturated with research that assesses different information quality attributes in the form of information completeness, accuracy, timeliness, representation, accessibility, currency, and many others [e.g. (Wang & Strong 1996; Eppler & Wittig 2000)]. This study proposes a uniform meta-examination of information quality taking into account the data capturing capabilities of the system under investigation.

Regarding the managerial implications, the proposed model may be applied to perform two distinct types of information quality assessment for an object tracking system. During an *a priori (or ex ante) evaluation*, the model may be employed to *assess the information quality requirements of a given context and to extrapolate pertinent design considerations*. This is particularly valuable taking into account that automatic identification and capturing technologies have, still, very high procurement and deployment costs. Thus, managers may use the model for decision making to evaluate the performance of alternative system configurations and deployment strategies for the Auto-ID technologies. Indeed, the information quality of an object tracking system varies depending on the selected configuration level of the system (such as, the locations that will be registered to the system as capture points, the adopted capturing technology per location and the object levels that the system will monitor). Arguably, the weight and importance of each capture point for the estimation of the degree of information quality for an object tracking system would be different. For example, in a retail store, placing two RFID readers that read products on item-level at the entrance and exit of the store's backroom might produce equal results compared to placing several RFID readers with the same reading capabilities to the backroom's shelves. The result in terms of information quality might be the same (100% accurate information regarding the inventory stock), but the costs are fundamentally different since the first deployment strategy requires less budget.

During an *a posteriori (or ex post) assessment*, the model may be applied to assess the information quality of an object tracking system and identify areas of improvement. In this context, designers may evaluate the design choices of the system in question in terms of deployment preferences (such as number of locations equipped with Auto-ID technologies and object levels to be monitored) and determine improvements based on design best practices of other similar system instantiations. Moreover, designers may evaluate whether the design choices of a deployed object tracking system meet the actual requirements of the application domain for information quality support. In this particular assessment type, designers may compare the a priori and a posteriori assessments of a system and spot deviations between the targeted and the implemented design choices.

We recognize that there is still ample room for improving and extending the model proposed in this article into a fully-fledged assessment framework for object tracking systems. Such a framework would propose associations among the degree of information completeness of a given tracking system and specific IQ-related dimensions. We are in the process of formulating a mathematical model to assess the accuracy, and timeliness of tracking information output relatively to the degree of information completeness of the system that is influenced from the system configuration preferences. We plan to use the integrated framework to provide comparative assessments of the information quality for different IT deployment strategies in the retail supply chain.

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