A Conceptual Framework and Belief-Function Approach to Assessing Overall Information Quality

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Abstract: We work in an information economy, interact in an information society, and live in an information world. As information availability becomes commonplace, the ability to rapidly define and assess information quality (IQ) for decision-making provides a potential strategic advantage. Yet despite its importance and value, IQ is often ignored or its models and definitions non-intuitive, domain specific, ambiguous or lacking important concepts. A readily applicable, simple and intuitive model bridging features of other key IQ models and addressing pre-existing problems is needed to facilitate assessment. We present such a model based on a user-centric view of IQ adapted from Wang et al. (1995), and discuss its extensions.

The model consists of four essential attributes (or assertions): 'Accessibility,' 'Interpretability,' 'Relevance,' and 'Credibility.' Four elements lead to an evaluation of credibility: 'Accuracy,' 'Completeness,' 'Consistency,' and 'Non-fictitiousness.'

IQ assessment is analogous to audit by evidence aggregation. We anticipate users will be more able to assign comfort or assurance levels to quality parameters based on evidence. Such assignments are readily modeled with belief functions, but not a probability framework. Expression of audit evidence has also been demonstrated to best follow a belief function framework. Therefore we present our model as an evidential network under the belief-function framework to permit user assessment of quality parameters. Several algorithms for combining assessments into an overall IQ measure will be explored. Examples in the domain of medical information are given.

I. Introduction

We work in an information[1] economy (Neef, 1998), interact in an information society, and live in an information world (Stonier, 1991). Identification and management of corporate

[1] We refer to a model of information (Bovee, M.W. and Srivastava, R.P, 2001) that encompasses input and data – simple information – as well as more complex and typically recognized forms of information.

information has become a specialized business sub-discipline, but availability of information alone is no longer a strategic advantage – quality of information is (Huang et al., 1999). We implicitly depend on the quality of the information we use in decisions, yet poor quality information is a source of lost productivity or failed enterprise (Huang et al., 1999; Wand & Wang, 1996; Wang & Strong, 1996; Strong, Lee & Wang, 1997). For sources such as the Internet, the quality of information available is of serious concern and its uncritical use poses serious risks. Biermann (1999) and Silberg (1997) cite glaring omissions and inaccuracies in online medical information.

Despite its importance and value, the quality of information from many contexts is often variably or loosely defined, or simply ignored (Fox et al., 1994; Huang et al., 1999; Wang, Storey, & Firth, 1995). Yet a means to assess information quality (IQ) for decision-making is vital. Without clearly defined attributes and their relationships, we are not just unable to assess IQ, we may be unaware or incapable of dealing with the problem. We need to understand the attributes of IQ and to have a broadly applicable, meaningful way to combine them into a single measure of quality. Unfortunately, pre-existing models contain various problems that hinder this: limitation to a specific view of information or quality, missing attributes, and confusion or dependence between attributes and their elements. For example, one well-known product-oriented model of IQ (Wang, Reddy and Kon, 1995) presents a key IQ attribute of Believability, with an element of source credibility. Yet something that is credible is defined as having sufficient evidence to be believed (American Heritage Dictionary, 1992), and thus there is circularity between the levels. Also, since evidence of source credibility may be assessed without examination of the information itself, any weight placed on credibility occurs at the wrong level in the model. We elaborate this concept further in Section III.

In another example, a systems-oriented IQ model (Wand and Wang, 1996) evaluates many intrinsic aspects of information completeness and consistency, but fails to include an attribute such as 'non-fictitiousness', an important attribute of information from auditing (e.g., see Mautz and Sharaf, 1964). Non-fictitious information is neither false nor redundant. For example, a hospital's patient record database would violate a 'Non-fictitiousness' attribute if it contained: 1) records for one or more non-existent patients, 2) redundant (i.e. wrongly repeated or duplicate) patient records, 3) fictitious fields or 4) fictitious values for valid fields.

Moreover, an empirically determined model (Wang and Strong, 1996) mixes intrinsic and extrinsic attributes and also mixes quality attributes with items of evidence that provide a level of comfort or assurance that quality attributes are met. For example, 'Completeness' deals with an intrinsic attribute of the information whereas in Wang and Strong (1996) model it is classified under 'Contextual' quality criteria. Contextual criteria deal with the user's perspective of information such as 'Relevancy' or their level of comfort that criteria are met. To illustrate this point further, consider the earlier example of a hospital's patient record database. 'Completeness' implies that the database contains all the patients' records with values in all its fields and no patient records or field values are missing. A user who determines a record to be *sufficiently* complete for their purposes is making a judgment or evaluation based on evidence relative to fixed criteria.

Mentioned earlier, the second problem with the empirical model of Wang and Strong (1996) is the mixing of quality attributes with items of evidence. For example, 'Reputation' and 'Believability' are classified as intrinsic attributes of quality. But reputation is a piece of evidence supportive of one or more intrinsic quality attributes. An information source or provider with a good reputation should receive a higher level of comfort or assurance that our expected criteria for intrinsic quality attributes are met. A disreputable or unknown source should instead receive a lower level of comfort that such criteria are met. Also, believability is not an intrinsic attribute, as Wang et al. have classified it; rather it is an expression of comfort or confidence based on evidence that the intrinsic attributes are met (Srivastava, 2001). 'Objectivity' is another dimension classified as an intrinsic attribute in the empirical model. However, as an expression of lack of bias it refers to the information source or information-generating process, not the information. For example, suppose a hospital's patients' database contains a field termed 'personality.' This field may contain, the values: 'pleasant', 'average, and 'grouchy'. These values do not have objective measures. They are subjective judgments. But these values have still the same intrinsic quality attributes of, for example, 'Accuracy'. If a value is measured objectively, such as a patient's temperature, then the level of comfort that the value is accurate depends on the (typically high) reliability of the measuring instrument. However, when the value is measured subjectively, as in the case of 'personality', the level of comfort that the field value is accurate is not easily assessable. Thus, 'Objectivity' does not represent an intrinsic attribute of quality, but how the values are measured.

What is needed is an IQ model flexible enough to work across various domains and purposes of user interest, robust enough to capture criteria of interest and of importance to the user in the production process, with clearly defined theoretical constructs as dimensions for testing against consumer perceptions. A means of combining evaluations assigned to IQ criteria is also needed. This paper presents such a simple and intuitive framework that incorporates features of other key IQ models and addresses pre-existing problems of interdependence, omission and confusion within dimensions. The model is then described as an evidential network under the belief-framework for explicitly tracking user assessment of the level of assurance obtained for various quality attributes and combining them into an overall IQ assessment.

The remaining sections of the paper are as follows: information, quality and IQ definitions; discussion of the strengths and weaknesses of key existing IQ models; description of the modified IQ model; description of the modified IQ model as a evidential network; conclusions; and directions for future research.

II. Information and Quality

In this section we discuss the definitions used for information, quality, and information quality, and present a categorization of information quality views and models.

Information

The origin of the word *data* is a Latin noun, *datum,* meaning something that is given (Flexnor and Hauck, 1987). An alternate definition is "facts or *pieces of information*" (Flexnor and Hauck, 1987, pg 508, italics added). "Inform" means to give form or character (Davenport and Prusak, 1998; OED, 2001). Thus we use the definition that information is (Bohn, Davenport and Prusak, 1998; Flexnor and Hauck, 1987), or contains (Stonier, 1991), input or pieces of information (data) organized to some purpose[2].

[2] A detailed discussion of this within a molecular model of information, including input, data, information, and transformations between each stage can be found in Bovee, M.W. and Srivastava, R.P. (2001).

There are at least six different schools of thought regarding information (Table 1). Each embodies the concept of information as a signal with senders and receivers (Redman, 1996), and each is consistent with our treatment of information created from structured input or data.

Table 1. Information Schools of Thought. (Redman, 1996)

School	Perceptions
Information Management	Processed data
Infological	Knowledge or information used for decision making or action-taking
Statistical	Relevant part or summary of data from an experiment
Everyday Use	Message part that informs
Information Theory	Uncertainty reduction
Thermodynamic	Inverse of entropy

Some information definitions (e.g. Davenport and Prusak, 1998) invoke fitness for the user's purpose to discriminate data from information. This invites confusion between the structured information, which is stable across user contexts (Stonier, 1991), and its usefulness. Input needs to be organized to *some* purpose to be information, but not necessarily a specific purpose nor that defined by a given user. Fitness of use for the domain and purpose of interest to the user defines information *quality*, not information. Otherwise, we should recognize "useless information" as an oxymoron.

Quality

There is long-standing support for the user-centric, product-oriented approach to defining quality (Juran, 1989; Deming, 1982; Garvin, 1987; Huang, 1999; Wang and Strong, 1996), and there is intuitive simplicity in the approach. Fitness of use as an IQ definition also has an additional advantage. Since information is highly fungible – the same information may be used by consumers with widely variant purposes and grossly dissimilar domains of interest – we need a highly flexible, consistent definition. Unlike other products, typically assessable quality dimensions and their criteria for the definition of fitness for use (Garvin, 1987) applied to information are absent or radically different.

Information Quality

Just as there are multiple perspectives or approaches to the concepts of information and quality, there are multiple views on what defines IQ or its dimensions (see Table 2 for details). These vary based on the definitional approach to quality (intrinsically or extrinsically defined) as well as the model of information (theoretical, system or process output, or product). Theoretical models (e.g. Wang, Reddy and Kon, 1995) define IQ conceptually based on introspection and logical analysis. Process-focused models (e.g. Kinney, 2000) view information as a by-product of measurement. If the measurement process is accurate and properly applied according to user requirements, then the resulting output is expected to be quality information. System-focused models center on specifying the many views and formats involved in the collection, storage, retrieval and display of information (Redman, 1996) such that the information that results from the process or the system should correctly represent the real-world view of interest to the user (e.g. Wand and Wang, 1996). A user-centric model (e.g. Wang and Strong, 1996) defines quality information as meeting user needs according to external, subjective user perceptions.

Table 2. Information and Quality Model Perspectives.

Information Model	Theoretical	System/Process Oriented	Product Oriented; User-Centric
Quality View	Intrinsic		Extrinsic
Information View	Intuitive		Empirical
Information Quality	Conceptually derived w/theoretical explication	Depends on system or process design to replicate the user's requirements or world view	Based on user perception

Each of these views has its strengths and weaknesses. Theoretical models provide good explication of constructs and relationships that are grounded in the literature, but they tend to treat quality as an objective construct, ignoring user perceptions. Systems- and process-oriented models tend to capture more details specific to intrinsic attributes of information, but view information as a process output or byproduct. User-centric models capture the broader range of attributes described as important by information consumers, but do not provide clearly defined constructs for these attributes. But, just as there are common dimensions for determining the quality of a type of wood for a given use, despite the plethora of types and uses available (grain, color, hardness, cost, rarity, etc.), general attributes applicable across domains and purposes of interest to information users may provide stable dimensions for assessing its quality.

III. IQ Models, Problems and the Modified Conceptual Framework

To determine and evaluate IQ criteria we take the perspective of an information user and outline the basic things we require for an information product to be useful. In the process we discuss these criteria relative to key IQ models and the significance of any differences. To clarify the model dimensions and criteria and any comparisons we use the example of a medical patient's clinical evaluation report.

The model may be summarized by a simple, ordered mnemonic of the main criteria: **AIRC** – **A**ccessibility, **I**nterpretability, **R**elevance, and **C**redibility (Table 3).

Table 3. Basic Aspects of Information Quality Conceptual Framework.

Criteria		**Basic Description**
A	Accessibility	Ability to retrieve information
I	Interpretability	Understandability and meaningfulness of information to the user
R	Relevance	Applicability of information to the user's domain and purpose of interest
C	Credibility	Degree of belief assigned by the user to information based on whether intrinsic attributes of *Accuracy, Completeness, Consistency and Non-fictitiousness* are met

Briefly outlined, to determine the quality of information – its fitness for our use – we must: 1) be able to get information which we might find useful (*Accessibility*); 2) be able to understand it and find meaning in it (*Interpretability*); 3) find it applicable to our domain and purpose of interest (*Relevance*); and 4) believe it to be credible (*Credibility*). Note that as an information user we would dismiss or discount information that meets our criteria for all but one of any of the above aspects, each of which may be more than just a binary value. We next describe these major aspects and their respective elements below, and discuss them relative to other key IQ models. Since our reasoning and model closely parallel that of Wang, Reddy and Kon (1995), we especially note important differences with that model. Explanatory examples are given from the domain of medical information (see also Table 4).

Accessibility

First we must be able to get information for it to be of use. IQ models that focus on information as a by-product of the system rarely cite information accessibility as a quality criterion (Wang, Storey and Firth, 1995), yet it is obviously critical to the user (Wang, Strong & Lee, 1997; Wang, Reddy and Kon, 1995; Wang & Strong, 1996). Information retrieval may require a certain amount of time or have an associated measure of cost to the user[3]. If information is inaccessible, all other qualities of it are irrelevant.

A hospital medical report on the outcome of patient surgery may not be needed any sooner than the end of the month for statistical purposes, or it may be needed immediately for reference and review during an examination. Off-site clinical access to such information may be free, available as for-pay products or services, or part of a private intranet. To access even different in-house information sources within a hospital intranet may also require widely different times, and have associated costs. Depending on their setting, a physician might conceivably have to decide between results only on hand, available by mail, by fax, or by electronic transfer, and the delays and costs associated with each choice.

Interpretability

Second, we must be capable of understanding any information retrieved (it must be intelligible) and if it is understandable we need to be able to derive meaning from it. Intelligible information is *capable* of being understood by the user and meaningful information conveys to the user some sense, significance, or meaning (American Heritage Dictionary, 1992; Flexnor and Hauck, 1987; OED Online, 2001). System-focused IQ models tend to assume interpretability of output information is inherent in the correct specifications of the system, the database design or the data production process (Wang, Storey and Firth, 1995; Wand & Wang, 1996; Kinney, 2000). Wang, Reddy & Kon (1995) describe interpretability as the understandability of the syntax and semantics of information. Yet this is the bare minimum of intelligibility – users may place much broader demands on the interpretability of information (Wang & Strong, 1996), ranging to practically requiring that “the thing speaks for itself” (Lieberman, 2000). If information is either unintelligible or meaningless to us, all its other qualities are irrelevant.

Unintelligible or meaningless information to one user may be intelligible or meaningful to another. The information embedded or created in its structure has not changed, but its quality differs according to user-determined criteria. For example, the same medical report of a patient’s blood chemistry could be written in either English or Japanese. To a physician who could not read it, the Japanese report would be unintelligible and meaningless. However, a physician fluent in both languages might find either report equally suitable. Intelligibility is a necessary but insufficient condition for interpretability. Consider the case in which a patient who wants to know the results of their medical check-up finds the clinical report to be intelligible (i.e. in readable English), but meaningless because they lack the ability to derive meaning from it.

[3] Some may treat time and cost as synonymous, but we contend that these instances are ones in which time is so dominant a factor that cost is disregarded, or the information is free. Nonetheless, the user is free to evaluate information sources for their quality of accessibility according to their needs.

Intelligibility and meaningfulness are user-defined IQ criteria. The actual content of the information does not depend on the user, nor on the quality ratings they assign. Thus interpretability is composed of both intelligibility and meaningfulness, with intelligibility the cusp of meaningfulness.

Relevance

Third, if we have information that we can understand and interpret, we want it to be relevant based on our user-specified criteria for the domain of interest and timely to our purpose within that domain. Of course, the user-specified criteria depend on the domain and purpose in mind. For example, if a surgeon performing a surgery wants to know about the patient's potential allergic reactions to anesthesia, a database providing all the information on the patient except that would be of no use. The information may be 'Accessible' and 'Interpretable' but not relevant in terms of user-specified criteria. *Relevance* has many possible domain- and purpose-related criteria, but if the information is outdated it is useless. Thus, timeliness is an important element of 'Relevance' as discussed below.

Wang, Reddy & Kon (1995) subsume relevance under the dimension of usefulness and treat timeliness as a separate usefulness criterion. However, it seems unlikely that information could be inaccessible or unintelligible, but still useful. Also, fitness for use is the global quality evaluation being made and decomposed by the model into specific criteria. Therefore usefulness is an inappropriate label, or is placed at the wrong level in the model. Also, while information could certainly be timely but irrelevant, the reverse seems unlikely, thus the criteria are not separable.

Timeliness has two components: *age* and *volatility* of the information. Age, or 'currency' of information is simply a measure of how old the information is based on how long ago it was recorded. All other things being equal, the more recently the information was collected, the more likely it is to be relevant. For example a medical report containing a patient's blood pressure values measured at their annual physical can be considered a current measurement for purposes of evaluating long-term health status. However, if a physician were to want to know the patient's blood pressure now, a more recent measurement is preferable. Volatility of information is a measure of information instability – the frequency of change of the value for an entity attribute of interest (the 'source value'). The more volatile information is the more rapidly *any* recorded values[4] become outdated. Non-volatile information is stable; it does not change nor become outdated. Again, for annual physical exams the information remains valid for one year, and for routine check-ups such periodic measures of blood pressure are satisfactory. But, during surgery, blood pressure values are much more briefly valid, more volatile, and must be monitored continuously to provide information on the patient's moment-to-moment status. Annual values are, of course, irrelevant in this context.

The datedness of information varies directly with its age and inversely with its volatility. Information must be updated as frequently as the source value changes or else become outdated. However, information that is updated as frequently as the source value changes may not be necessary for the user's purpose, nor practical, feasible or cost-effective. Thus, a relative measure of outdatedness – *timeliness* – becomes an important IQ sub-element. *Timeliness* is a

[4] Other than continuously recorded real-time information, which is the opposite extreme to non-volatile information.

judgment by the user of whether information is recent enough to be relevant, given the rate of change of the source value, and the domain and purpose of interest.

If information is updated frequently enough for the user's purposes then it is timely. If not, it may be irrelevant. The less timely information is, the less likely it is to be relevant to the user. For example, a doctor may require their recovering surgery patient to only have twice-daily blood pressure measurement, even though the underlying value varies continuously. Every twelve hours, the prior blood pressure measurement becomes outdated information and becomes less timely[5]. If the next measurement is not made on time, the most recent (i.e. least outdated) may suffice. Measurements from a week ago, however, are certainly no longer timely at all and therefore of unacceptable quality.

Users of historical information may need information from a specific point or period in time; this is different from timeliness. One can require relevant blood pressure information to include measurements from surgeries during a specific week last year *and* that were timely when recorded.

Since information may be relevant, but inaccessible or unintelligible, we use relevance as the dimensional label, and timeliness as one specific user-determined criterion among the many possible. This matches the loading of relevance and timeliness as factors important to Contextual Quality in the empirical model by Wang & Strong (1996). Information that does not match the domain or purpose of the user is presumed useless, and information that does but is outdated is similarly useless.

Credibility

Last, given access to interpretable, relevant information we require it to also be credible. Credibility of information exists when the information is plausible, when there is sufficient reason for it to be believed by the user (American Heritage Dictionary, 1992; OED Online, 2001). This dimension corresponds most closely with aspects of information frequently considered for quality measures and thought of as intrinsic to the information itself (Wang, Storey & Firth, 1995; Wang, Reddy & Kon, 1995), or as stemming from the system design or processing of information (Wand & Wang, 1996). We consider information that is accurate, complete, consistent (Wang, Reddy & Kon, 1995) and non-fictitious (Mautz and Sharif, 1964) to be credible.

Several IQ models have categorized these criteria under dimensions other than the intrinsic nature of information (Wang, Strong & Lee, 1997; Wang & Strong, 1996). This may be the result of confusion due to the dominance of user-definitions for virtually all quality criteria once fitness for use is established as the global quality standard. Other IQ models subsume information source credibility under the dimension of believability (Wang, Reddy & Kon, 1995). As discussed earlier, credibility of an information source is evidence attesting to IQ, not an attribute of the information itself. Even though source credibility may be a criterion used by an information user (Wang and Strong, 1997), it seems more likely to be used as a heuristic or proxy for the global dimension of believability, not as a criterion for it. This can be seen upon

[5] We recognize that the meaningfulness of the information may, in part, be derived in context with other values in a time series. Thus the first of two serial measurements may actually derive more relevance after the second is obtained. However, with successive new measurements the earlier ones become more outdated, less timely and less relevant.

examining the definition for "credible" (American Heritage Dictionary, 1992). Given a credible source, other evidence – accuracy, completeness, consistency and non-fictitiousness of the information itself – may be assumed, not evaluated. Thus evaluations of source credibility should enter the model at the same level as the main dimension, as evidence in support of it rather than valuations of elements that compose it (e.g. 'third party assurance' in Figure 4).

To avoid a circular definition between attribute and element we substitute *Credibility* for *Believability* and leave evaluations of the source outside of the model for the time being. Information that is retrievable, intelligible and meaningful, and relevant, yet lacks all credibility, would be useless. Credibility has four elements: Accuracy, Completeness, Consistency, and Non-fictitiousness.

<u>Accuracy</u> deals with information being true or error free with respect to some known, designated or measured value. As part of a patient examination, the patient's name is known and therefore comparable for accuracy to information that should contain it. The patient's identification number is designated and may be checked for accuracy against the algorithm or context from which it was derived. Lastly, the patient's blood pressure can be measured directly to determine if the recorded value and the measurement are the same or sufficiently close for the user's purposes. Accuracy plays a major role in most models of IQ (Wang, Storey & Firth, 1995) as an intrinsic attribute of the information itself. Yet establishing accuracy is difficult if not impossible in many circumstances, and what is acceptable or desirable information accuracy still requires judgment on the part of the user.

<u>Completeness</u> deals with information having all required parts of an entity's information present (Wang, Reddy & Kon, 1995; Wang, Storey & Firth, 1995). A patient examination report example typically requires descriptive patient information such as name, age, sex, treatment and payment details, plus the results of various visit-specific tests and any pertinent diagnoses. Absence of any of these renders the report incomplete, unless there is tolerance for missing values for some attributes. In a database environment, completeness can be in violation if a patient or patients' records are missing or certain field values are missing.

<u>Consistency</u> of information requires that multiple recordings of the value(s) for an entity's attribute(s) be consistent across time or space (Wang, Reddy & Kon, 1995; Wang, Strong & Lee, 1997). To be consistent these values must be the same in all cases (for discrete values) or closely grouped in dispersion (for continuous values). Although consistency appears frequently as a proposed quality dimension (Wang, Storey & Firth, 1995; Wand & Wang, 1996), it does not appear as a prominent feature of empirically assessed user models of IQ (Wang and Strong, 1996).

Hospitals often store information for different departments separately, and the patient records for a male admitted in one department and tested in another should both have the discrete value "Male" recorded for his gender. Having "Female" recorded in one would be both inaccurate in the single case, and inconsistent with all other sources. If this patient's blood pressure was measured once and recorded several places, it should be the same in all instances. The patient's blood pressure measurements taken several times at a single visit, or multiple times across departments on the same day, should be tightly dispersed.

Lastly, <u>non-fictitiousness</u> is an important intrinsic attribute of information as used in auditing (e.g., see Mautz and Sharaf, 1964). Non-fictitious information has no false or redundant entities, fields, or attribute values. As mentioned earlier, the 'Non-fictitiousness' attribute would be in violation if the database contains: 1) one or more records for patients record(s) that does (do) not exist, 2) redundant records for certain patients, i.e., certain patient records are repeated, or 3) fictitious value(s) in certain field(s). No IQ model directly addresses all aspects of this problem. Wand & Wang (1997) present a system-oriented model that most closely approximates this, discussing meaningless combinations of information (information not corresponding to the real world) and incorrect information (information wrongly mapping to the real world). However, fictitious information is not necessarily meaningless and can correspond to the real world. In fact, a goal of deliberately falsifying information is to undetectably simulate a real-world state that *could* occur, but did not. Another type of fictitiousness is redundancy. Redundant information is permissible in some systems models of IQ (Wand and Wang, 1997), yet leads to ambiguity wherein at least one item of information should not exist but it may be difficult to discern which is false. Establishing non-fictitiousness as a measure of credibility is an important auditing process.

Thus, our conceptual model of IQ (Figure 1) consists of three essential extrinsic attributes (or assertions): ‘Accessibility’, ‘Interpretability’, and ‘Relevance’, and one intrinsic attribute (or assertion): ‘Credibility.’ The extrinsic attributes determine the user perceived quality attributes and the intrinsic attribute, “Credibility’, determines the internal aspect of quality of information, which consists of five elements (or sub-assertions): ‘Accuracy’, ‘Completeness’, ‘Consistency’, and ‘Non-fictitiousness’.

IV. Evidential Network for Assessing IQ

Srivastava and Mock (2000) have developed an evidential network for WebTrust assurance services for the purpose of evaluating whether the Webtrust assurance criteria have been met. If the evidence gathered in the process provides a sufficiently high level of confidence (0.95 on a scale of 0-1) that the WebTrust criteria are met, then the assurance provider could issue an unqualified (i.e., clean) opinion on the service. A similar evidential network approach has been applied by Srivastava, Dutta and Johns (1996) in the audit process of a healthcare unit. There are basically three issues in such evidential network approaches. First is the relationship among the variables (i.e., assertions or sub-assertions) in the network. Second is the structure of the evidential network, which in essence requires the knowledge of what piece of evidence relates to what assertion or assertions. The network structure arises due to the fact that one item of evidence may pertain to more than one assertion or sub-assertion. The third issue deals with the representation of uncertainty involved in the judgment of whether a certain variable or attribute is met, at what level of confidence, based on the evidence collected. The first issue really deals with understanding the problem at hand. In other words, one needs to know the main variables (assertions or attributes) of the network and their interrelationships. In our case, the attributes that determine the quality of information are given in Figure 3.

Srivastava and Mock (2000) and Srivastava et al. (1996) have used Dempster-Shafer Theory of belief functions (Shafer, 1976) to represent uncertainties in the evidence. They have argued (Srivastava and Shafer, 1992) that belief functions provide a better framework for representing uncertainties in the evidence encountered in the situations faced by auditors or assurance provided. A recent study by Harrison et al. (2001) in auditing and a study by Curly and Golden (1995) in psychology provide further evidence in support of using belief functions for representing uncertainty in evidential reasoning. We take the same view and argue that belief functions would better represent uncertainties associated in assessing the quality of information.

Figure 4 represents an evidential network for IQ measurement. The rounded nodes represent variables in the network. These variables are: "Information Quality" (IQ), the extrinsic and intrinsic attributes AIRC (Accessibility, Interpretability, Relevance, and Credibility), the components of relevance: 'Timeliness' and 'User-specified criteria', and the components of Credibility: 'Accuracy', 'Completeness', 'Consistency', and 'Non-fictitious'. The circle with '&' inside it represents an 'and' relationship[6] between the variable on the left of it with the variables on the right. For example, the main variable 'IQ' is connected to the four variables AIRC on the right through an 'and' relationship. This implies that IQ is met (i.e., IQ is high) if and only if all the variables on the right are met (i.e., each has a high level of confidence that it is met). If any one of them is not met (i.e., it takes a low values) then IQ is not met (i.e., IQ is low).

The rectangular boxes represent items of evidence pertinent to various attributes as represented by direct linkages between items of evidence and the attributes. In order to determine the overall quality of information, one needs to gather the relevant items of evidence as indicated in Figure 4, evaluate the level of support each item of evidence provides to the corresponding variable(s), and then aggregate these assessment of support in the network to determine the overall level of support for the value 'high quality' of IQ. Expert opinion regarding evidential inputs to the model will be gathered. We will then use a computer system known as Auditor's Assistant developed by Shafer, Shenoy and Srivastava (1988) for combining items of evidence in a network of variables similar to Figure 4 where judgment of uncertainty is expressed under belief functions.

Using the above software, we plan to perform the following sensitivity analyses:

1. Determine how sensitive the output result is with regard to changes in the input values.
2. Determine whether one can use non-numerical inputs (e.g. very high, high, medium, low, very low) based on some range of numerical values and test the sensitivity of output values.
3. Determine which item of evidence is the most significant for the overall IQ.
4. Determine sensitivity of the relationships among variables on the overall IQ. We will use the following relationships: 'and', a combination of 'and' and 'or', and an averaging relationship.

V. Summary, Conclusion and Directions for Future Research

The modified IQ model presented here extends and bridges previous models, resolving ambiguities in terminology and relationships of quality attributes. In particular: judgments of information source credibility exist independently of information attributes and must therefore enter from outside any information model; 'believability' and 'credibility' cannot be independent quality attributes nor an attribute and related element as they are circularly related; 'credibility' is a global assessment based on one or more judgments and belongs at a high level within the quality model; information timeliness is an element of relevance to the user, not independent from relevance; and, although aspects of it are found in systems-oriented data quality models, non-fictitiousness as found in auditing is an important concept absent in other IQ models. In the theoretical introduction to the model we have also clarified a potentially critical ambiguity in the

[6] At the moment we are only considering 'and' relationships among the variables as considered by Srivastava and Mock (2000) and Srivastava et al. (1996). Such a relationship makes sense, especially when all the attributes are essential in order for the main objective to be met. Other relationships will subsequently be tested.

definition of information by proposing that usefulness does transform data to information, nor a define a characteristic of information itself, but is a judgment of IQ. This and the clarifications above provide the theoretical foundation to permit our modified model, which forms the structure for evidential network, to then be used to evaluate overall IQ. Toward this end, we have proposed several evaluative steps to be taken in determining appropriate relationships among the network variables, including several different rules of combination.

Testing of the logical implementation and behavior of the network, however, needs to be supplemented with investigations of its applicability for information consumers (as it is designed as a *user-centric* model). We intend to empirically evaluate the network structure and attributes with information users' direct assessments of IQ. While the models that form the foundation for our modifications represent a broad range of approaches (and of users in one case), the needs or concerns of specific groups may not be properly represented by a general model. As evident through the examples and discussion, future research will focus on the perceived IQ needs of two related groups – clinical and Web information users.

In addition, applicability of the model requires evaluation through field-testing. Given the concerns with the Web information quality (health information in particular), the evidential network could be used for rating website IQ through an online interface and user feedback collected to evaluate the tool. While at least one such IQ rating tool is available (MITRETECH, 1999), it does not use belief functions for representing nor aggregating users' ratings. As discussed earlier, the belief function formalism appears to be the best way to represent such judgments.

Lastly, given the global explosion of information availability and the apparent concerns regarding online information quality, we see a need for a robust model of IQ expressed in XML. As bandwidth and processing speeds increase, a theoretically and practically proven model of IQ holds great promise as a taxonomy for metadata tags that do away with the need for manual user evaluations of IQ.

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Figure 1: Wang, Reddy and Kon (1995) Model of Data Quality

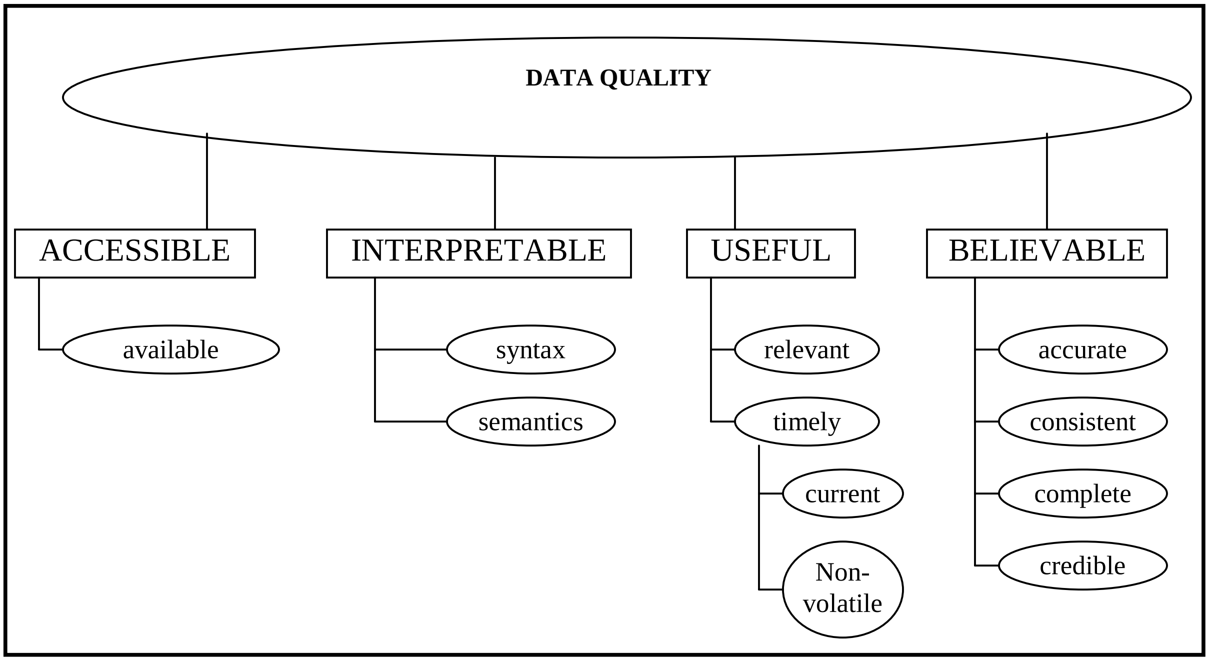

Figure 2: Wang and Strong (1996) Model of Data Quality

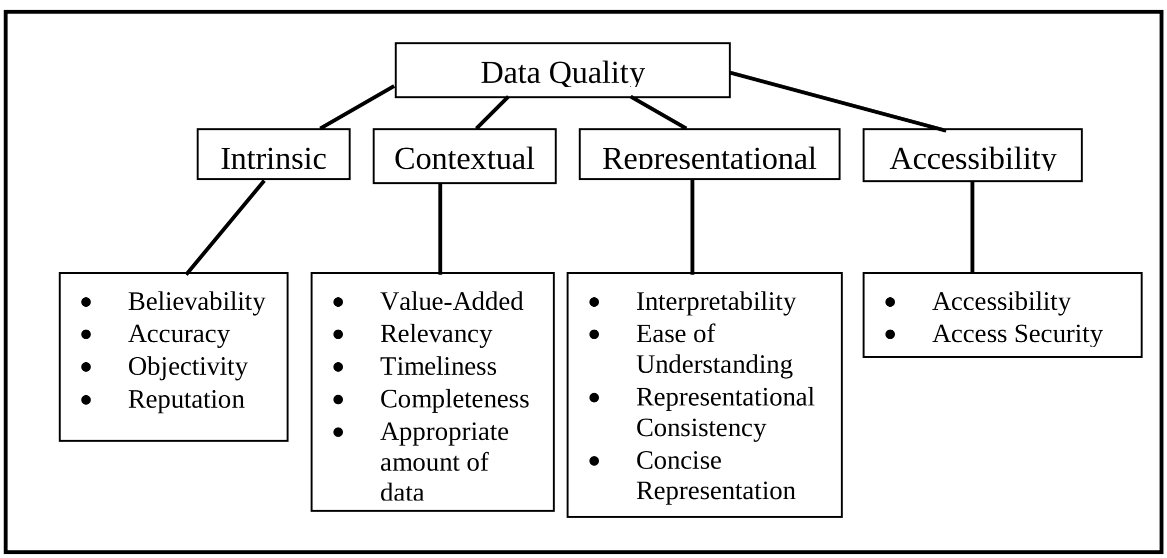

Figure 3: IQ Model Proposed in the Present Study

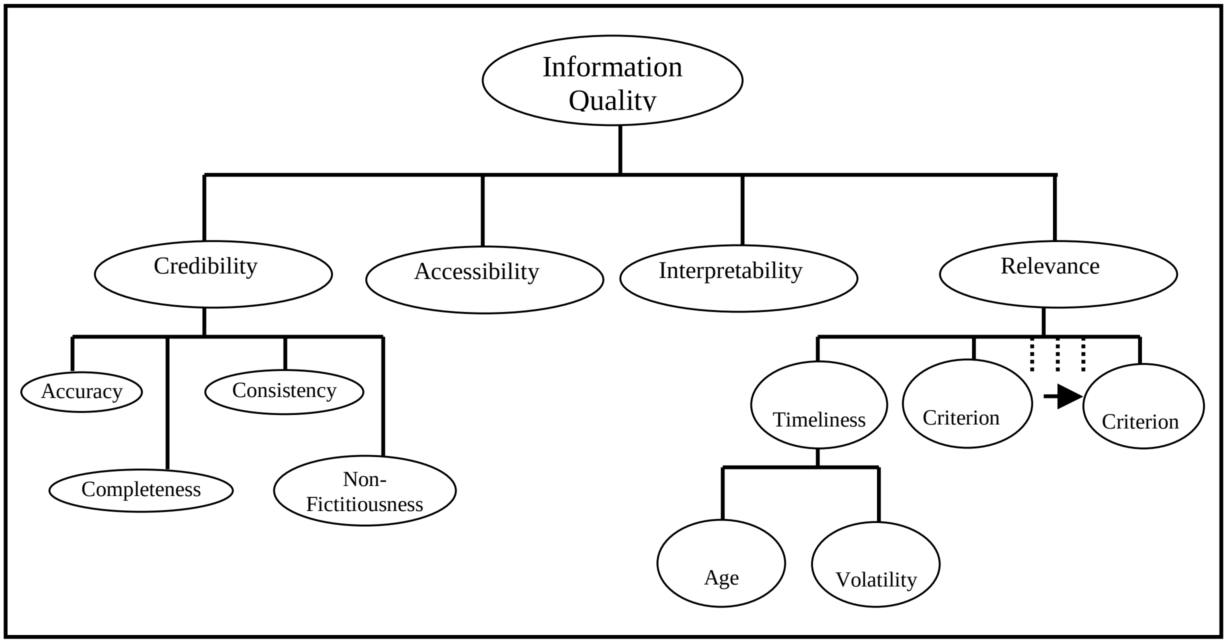

Figure 4. Evidential Network of Information Quality Attributes and Elements

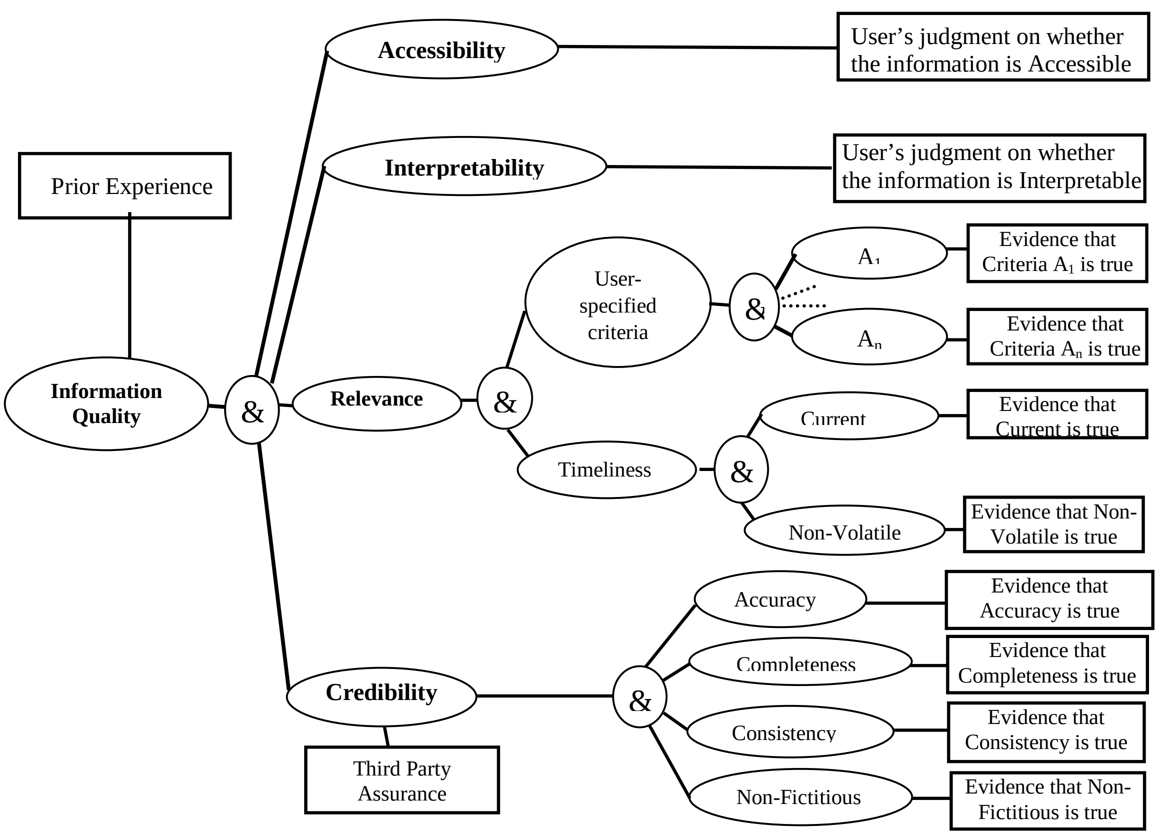

Table 4: IQ Attributes and Their Elements with Explanations and Examples

Attribute	Elements	Sub-Elements or Cases	Explanation/ Definition	Example
Interpretability	Intelligibility	--	Capable of being understood, apprehended or comprehended.	A routine hospital report of the results of a patient's physical examination should be legible and intelligible. If, by accident, it were printed in ASCII code it would not be, even though it still contained the same information.
	Meaningfulness	--	If intelligible, the information has some minimum level of meaning *to the user*. The meaning content may be increased by adding structure or organization.	A patient examination report printed as a continuous string of words and values may barely be meaningful, but organized into tabular format it becomes more easily interpretable and meaningful.
Accessibility (retrievable)	Time		How long it takes to retrieve the information	Time needed to assemble in-house patient test information; lag-time for Internet replies to search queries; download time for files
	Cost		How the user measures the cost of retrieving the information.	Manpower needed to gather and assemble the information; price charged for an information product or service

Table 4, Continued: IQ Attributes and Their Elements with Explanations and Examples

Credibility (plausible or believable)	Accuracy	Known	True or error-free w/respect to some known value	The recorded patient name matches the known patient name
		Assigned	True or error-free w/respect to some designated or assigned value	The recorded patient number matches the assigned patient number
		Measured	True or error-free w/respect to a measured value	The recorded patient blood pressure value is within plausible limits, normal ranges, or is corroborated by other patient information
	Completeness		All required parts present; all attributes needed are present; no missing records; some tolerance for missing values	Patient information typically includes name, age, sex, treatment, and payment details, plus the results of various visit-specific tests. Interpretation of the results may be impaired if any are missing.
	Consistency	Discrete	Same value across all cases	A male patient should be recorded as a male in all departments and for all tests within a hospital
		$Continuous_1$	Same value across multiple occurrences	A single measurement of a patient's blood pressure, recorded in multiple places should be the same in all instances
		$Continuous_2$	Tightly dispersed values across multiple measures	Blood pressure measured multiple times w/in a short time should be close to some average of the true value
	Non-Fictitiousness	Records	No false or redundant records exist	No patient record should be completely identical to any other; each patient record should represent an actual patient hospital visit
		Attributes	No false or redundant attributes exist	No patient attribute should be completely identical to another; each patient attribute should represent an actual patient attribute
		Values	No false values exist	All values for patient attributes should be actual
Relevance (user domain- and purpose)	User-specified	A_1	User-specified attributes derived from domain- and purpose-specificity	OSHA
		A_2		The hospital
		A_3		The department
		A_4		The doctor
		A_n		The patient
	Timeliness	Currency	Recentness of collection	Blood pressure may be measured annually or continuously
		Volatility	How long it remains valid	For general health check-ups, annual blood pressure readings are sufficient; for surgery it needs to be monitored continuously.