A REVIEW OF INFORMATION QUALITY RESEARCH

- DEVELOP A RESEARCH AGENDA –

(Completed Paper)

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Abstract: Recognizing the substantial development of information quality research, this review article analyzes three major aspects of information quality research: information quality assessment, information quality management and contextual information quality. Information quality assessment is analyzed by three components: information quality problem, dimension and assessment methodology. Information quality management is analyzed from three perspectives: quality management, information management and knowledge management. Following an overview of contextual information quality, this article analyzes information quality research in the context of information system and decision making. The analyzing results reveal the potential research streams and current research limitations of information quality. Aiming at bridging the research gaps, we conclude by providing the research issues for future information quality research and implications for empirical applications.

Key Words: Information Quality Assessment, Information Quality Management, Contextual Information Quality

INTRODUCTION

Information quality (IQ) research is motivated by IQ problems occurred in organizations. Numerous business initiatives failed and losses are generated because of IQ problems. For instance, a major financial institution is embarrassed because of a wrong data entry of an execution order of $500 million [55]. The space shuttle Challenger and the shooting down of an Iranian Airbus by the USS Vincennes are the results of IQ problems and IQ management errors [21]. From the cases above, we can observe that IQ problems are pervasive [55], costly [19] and even disastrous [21]. In order to prevent IQ problems, researchers have focused on different aspects of IQ research such as IQ assessment and IQ management.

Adapting the definition of quality, IQ can be defined from information consumer perspective and data perspective. The term quality has been defined as fitness for use [28] and this definition is widely adopted in the quality literatures [52]. From the viewpoint of information consumer, Wang and Strong [52] define IQ as the information that is fitness for use by information consumers. They argue that ultimately it is the consumer who will judge whether or not an information product is fitness for use. However, information consumers are not very capable of finding errors in information and altering the way they use the information [31]. So from the data perspective, IQ can be defined as the information that meets the specifications or requirements [29]. With the two major definitions of IQ, IQ research is divided into two communities: management and database [41]. By combining the two perspectives, Redman [44] points out that information is of high quality if it is free of defects and possesses desired features.

The objective of this study is to review three major aspects of IQ research: IQ assessment, IQ management, and contextual IQ. For each aspect, this paper provides state of the art for current IQ research and implications for future IQ research.

The paper is organized as follows: the next section provides an overview of this study and the scope of the review. The following three sections discuss three aspects of IQ research: IQ assessment, IQ management, and contextual IQ. The final section provides a summary of IQ research issues and draws a conclusion of our work.

METHOD

Most of the IQ research falls into answering the following research questions: (1) how to assess IQ? (2) how to manage IQ? and (3) how does IQ impact organizational contexts? Accordingly, this review concentrates on three aspects of IQ research: IQ assessment, IQ management and contextual IQ. IQ assessment contains three key components: IQ problem, IQ dimension and IQ assessment methodology. IQ assessment methodology employs a set of IQ dimensions which are linked to different IQ problems. IQ management merges three realms of management: quality management, information management and knowledge management. Contextual IQ investigates IQ effects on various organizational contexts such as e-business, healthcare and accounting. This review focuses on two most cited contexts: information system and decision making. We describe the structure of the review using the following figure (figure 1).

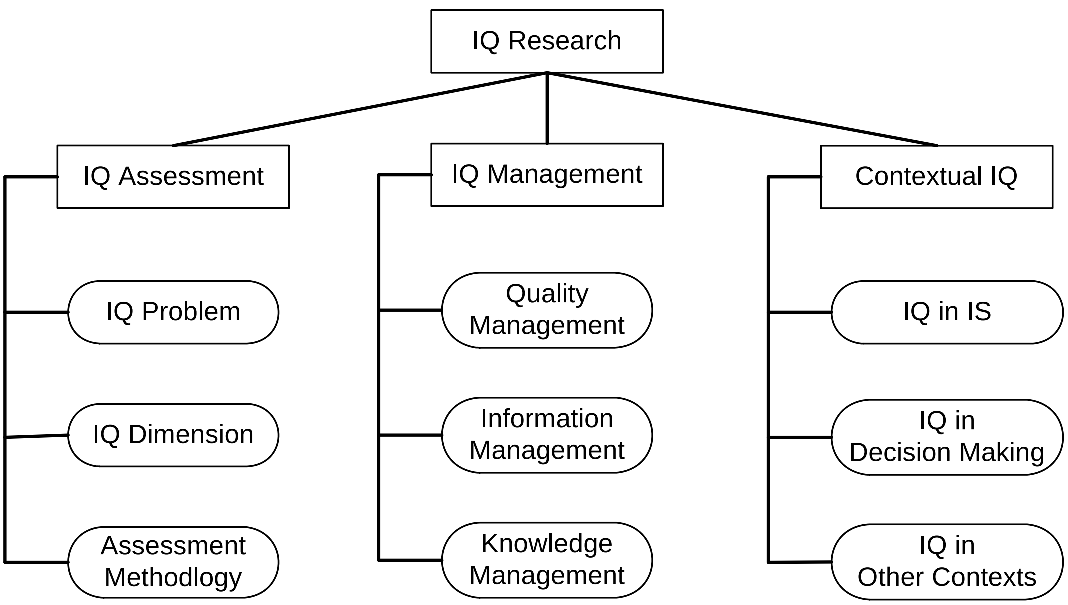


Figure 1: Structure of the review

According to the overview, we specify the scope of the review into the following elements: (1) Identification and classification of IQ problems. (2) Identification, definition, classification and dependency of IQ dimensions. (3) Evaluation of IQ assessment methodologies. (4) An overview of IQ management from the perspectives of quality management, information management and knowledge management. (5) A summary of IQ research in different contexts. (6) IQ research in information system. (7) IQ research in decision making. After the review in each element, we provide current IQ research issues and future IQ research indications.

IQ ASSESSMENT

Adapting the common definition of assessment [22], IQ assessment can be defined as the process of assigning numerical or categorical values to IQ dimensions in a given setting. Based on the literatures related to IQ assessment, we organize IQ assessment into three layers: metric layer, dimension layer, and methodology layer. Metric layer includes IQ metrics that represent different IQ problems. These IQ problems are classified by a “2 contextual views × 2 assessment views” model. Dimension layer comprises the IQ dimensions, which are characteristics of information. These IQ dimensions are connected to the corresponding IQ metrics. One dimension can link to multiple metrics and one metric can be linked to multiple dimensions. For example, while accuracy (IQ dimension) can link to incorrect data (IQ metric) and out-of-date data (IQ metric), out-of-date data (IQ metric) can be linked to accuracy (IQ dimension) and timeliness (IQ dimension). Once one IQ metric is linked to multiple IQ dimensions, it will cause the dependencies among these IQ dimensions. Methodology layer contains the IQ assessment models, frameworks and methodologies. These components in this layer will link to a set of IQ dimensions. We describe the discussion above by the following figure (figure 2):

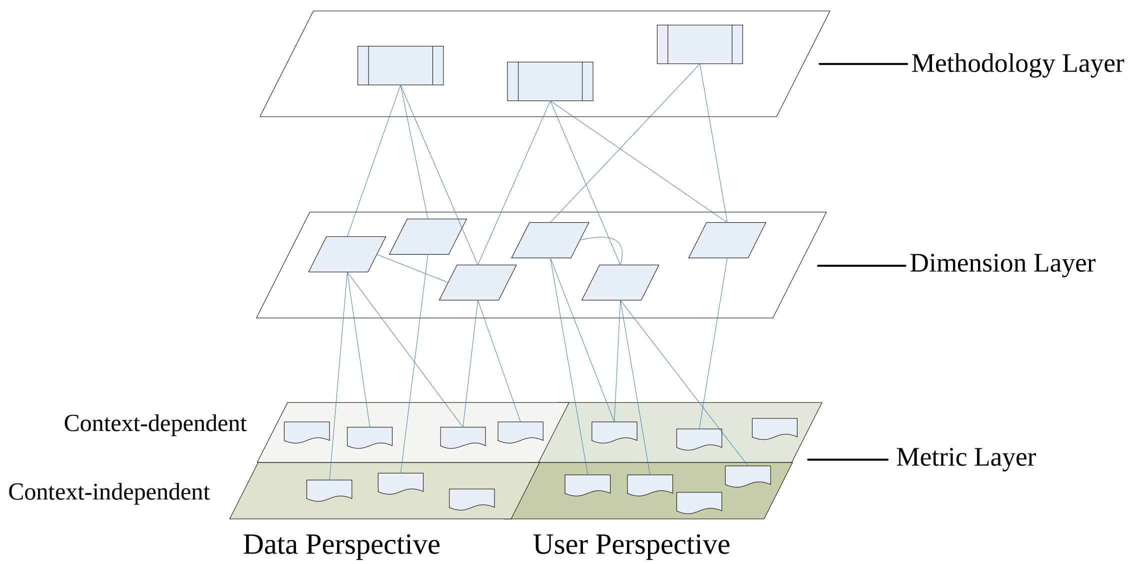


Figure 2: A framework for IQ assessment review

IQ Problem

A number of contributions have been done towards the identification of IQ problems. Garvin [23] points out three types of IQ problems: biased information, outdated information, and massaged information. Biased information means the content of the information is inaccurate or distorted in the transformation process. Outdated information is the information that is not sufficiently up to date for the task. Massaged information refers to the different representations of the same information. Lesca and Lesca [35] classify IQ problems into the product and process views. Product view focuses on the deficiencies of the information itself such as incompleteness and inconsistency. Process view concentrates on the problems that are caused in the information production and distribution process. In view of literatures related to IQ problems. We classify IQ problems by a two-by-two conceptual model. The columns capture IQ problems from data perspective and user perspective, and the rows capture IQ problems as context-independent and context-dependent. Using this model, we classify typical IQ problems which are identified by Garvin [23], Lesca and Lesca [35], Huang et al [24], Pipino et al. [42], Oliveira et al. [41], and Eppler [18].

	Data Perspective	User Perspective
Context-independent	❑ Spelling error [41], [18] ❑ Missing data [41], [18] ❑ Duplicate data [41], [18] ❑ Incorrect value [41], [23], [18] ❑ Inconsistent data format [41], [35], [18] ❑ Outdated data [41], [23], [18] ❑ Incomplete data format [41], [35] ❑ Syntax violation [41] ❑ Unique value violation [41] ❑ Violation of integrity constraints [41] ❑ Text formatting [41], [23]	❑ The information is inaccessible [24] ❑ The information is insecure [24] ❑ The information is hardly retrievable [24] ❑ The information is difficult to aggregate [24] ❑ Errors in the information transformation [24]
Context-dependent	❑ Violation of domain constraint [41], [42] ❑ Violation of organization's business rules [41], [42] ❑ Violation of company and government regulations [41], [42] ❑ Violation of constraints provided by the database administrator [41]	❑ The information is not based on fact [24], [23] ❑ The information is of doubtful credibility [24] ❑ The information presents an impartial view [24] ❑ The information is irrelevant to the work [24] ❑ The information consists of inconsistent meanings [24], [23], [35] ❑ The information is incomplete [24], [35] ❑ The information is compactly represented [24] ❑ The information is hard to manipulate [24], [18] ❑ The information is hard to understand [24]

Table 1: Classification of IQ problems

The four quadrants in the table above are described as follows:

- Data Perspective/Context-independent quadrant indicates the IQ problems in the database. These IQ problems can be applied to any data set.
- Data Perspective/Context-dependent quadrant indicates the IQ problems that violate the business specifications. These IQ problems can be detected by contextual rules.
- User Perspective/Context-independent quadrant indicates the IQ problems that may happen in processing the information.
- User Perspective/Context-dependent quadrant indicates the IQ problems that are not fitness for intended use by information consumers.

Regarding IQ problems, various methods can be applied to resolve these problems. From the data perspective, IQ problems can be resolved through data cleansing algorithms [39], data mining rules [48], statistical process control [24] or dictionary matching routines [47]. From the user perspective, IQ problems often cannot be resolved by automated processes [18] and these problems require optimization of resource allocation [6], analysis of business issues [53] [18], re-engineering process [43], or aligning information flow with the corresponding information manufacturing system [54].

IQ Dimension

Various studies have confirmed that IQ is a multi-dimensional concept [5] [43] [51] [52] [24]. Over the last two decades, different sets of IQ dimensions have been identified from both the database and management perspectives. We review IQ dimensions from the following aspects: identification, definition, classification, and dependency.

Identification of IQ Dimension

In the work of Wang and Strong [52], they propose three approaches to study IQ: intuitive, theoretical and empirical approach. We adapt these approaches to analyze the derivation of IQ dimensions. Intuitive approach derives IQ dimensions from the researchers' experience and demands of particular cases. In this approach, IQ dimensions are identified according to the specific application contexts. For example, O'Reilly [38] uses accessibility, accuracy, specificity, timeliness, relevance, and the amount of information to assess IQ in the context of decision making. Ballou and Pazer [5] employ accuracy, timeliness, completeness and consistency to model IQ deficiencies in multi-input, multi-output information systems. Theoretical approach generates IQ dimensions on the basis of data deficiencies in the data manufacturing process. For example, Wand and Wang [51] use an ontological approach to derive IQ dimensions by observing inconsistencies between real-world system and information system. Empirical approach provides IQ dimensions by focusing on whether the data are fitting for use to data consumers. For example, Wang and Strong [52] capture 15 IQ dimensions that are important to data consumers. Kahn et al. [29] select 16 IQ dimensions for delivering high quality information to data consumers. From the discussion above, we can observe that different sets of IQ dimensions can be identified using different approaches.

Definition of IQ Dimension

The three approaches above can also be considered as three perspectives of defining IQ dimensions. Intuitive approach defines IQ dimensions from the data perspective. For example, Ballou and Pazer [5] define completeness as all values for a certain variable are recorded. Theoretical approach defines IQ dimensions from the real-world perspective. For example, Wand and Wang [51] define completeness as the ability of an information system to represent every meaningful state of the represented real world system. Empirical approach defines IQ dimensions from the user's perspective. For example, Wang and Strong [52] define completeness as the extent to which data are of sufficient breath, depth, and scope for the task at hand. We express the perspectives of defining IQ dimensions in the following figure (figure 3).

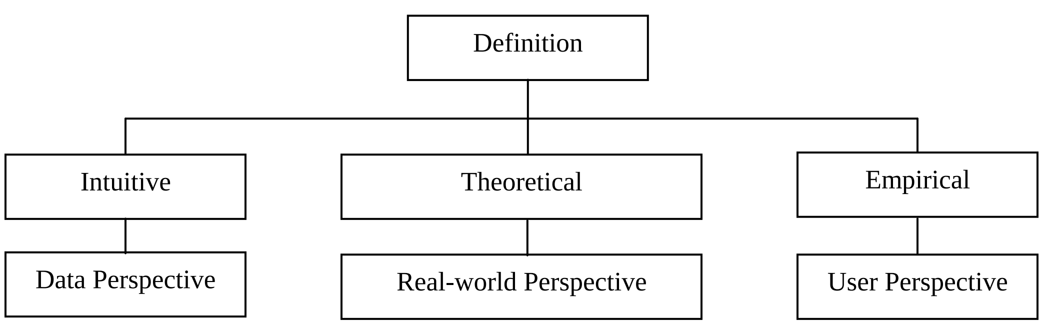


Figure 3: Definitions of IQ dimensions from different approaches

The advantage of using data perspective is that IQ can be controlled objectively and assessed automatically. The advantage of employing real-world perspective is that information is considered as products, which can be assessed objectively by a comprehensive set of IQ dimensions. However both two perspectives fail to capture the expectations of the data consumers. From the user perspective, the advantage is that more IQ dimensions can be derived from the users' expectations and IQ can be improved according to the intended use. However, this perspective fails to measure IQ automatically and is difficult to uniform the various assessment results from different data consumers.

Classification of IQ Dimension

Based on the identification and definition of IQ dimensions, researchers have proposed different kinds of approaches to classify the IQ dimensions. Wang and Strong [52] propose a hierarchical framework that consists of four categories of IQ dimensions: intrinsic IQ, contextual IQ, representational IQ, and accessibility IQ. Intrinsic IQ focuses on the quality of data itself. Contextual IQ emphasizes the IQ requirements in the specific contexts. Representational IQ centers on the utilization of the information such as interpretable and easy to understand. Accessibility IQ means the information can be accessible but secure. Wand and Wang [51] use the ontological approach to derive IQ dimensions and categorize them by internal view and external view. Internal view is use-independent and it contains a set of IQ dimensions that are comparable across applications. External view is concerned with the use and effect of the information system, which represent the real-world system. Naumann and Rolker [37] organize IQ dimensions by three main factors that influence IQ: the perception of the user, the information itself, and the process of accessing the information. These three factors can be considered as subjective, objective and process. Helfert [25] classify IQ dimensions by employing semiotics and two aspects of quality, which are quality of design and quality of conformance. Semiotics comprises three levels: syntactic, semantic and pragmatic. Syntactic level considers the basic representation of information. Semantic level focuses on the information related to real world objects. Semantic level deals with information processes and information users. Kahn et al. [29] develop a two-by-two conceptual model for describing IQ dimensions. Two rows are product quality and service quality while two columns are conformance to specifications and meeting and exceeding consumer expectations. So IQ dimensions are considered into four quadrants: sound, dependable, useful, and usable. Bovee et al. [12] present a categorization of IQ dimensions by the sequence of using information. The sequence includes the following four aspects: obtaining the information (accessibility), understanding the information (interpretability), the information is applicable to the given context (relevance), and the information is free of error (integrity). We summarize the discussion above into the following figure (figure 4):

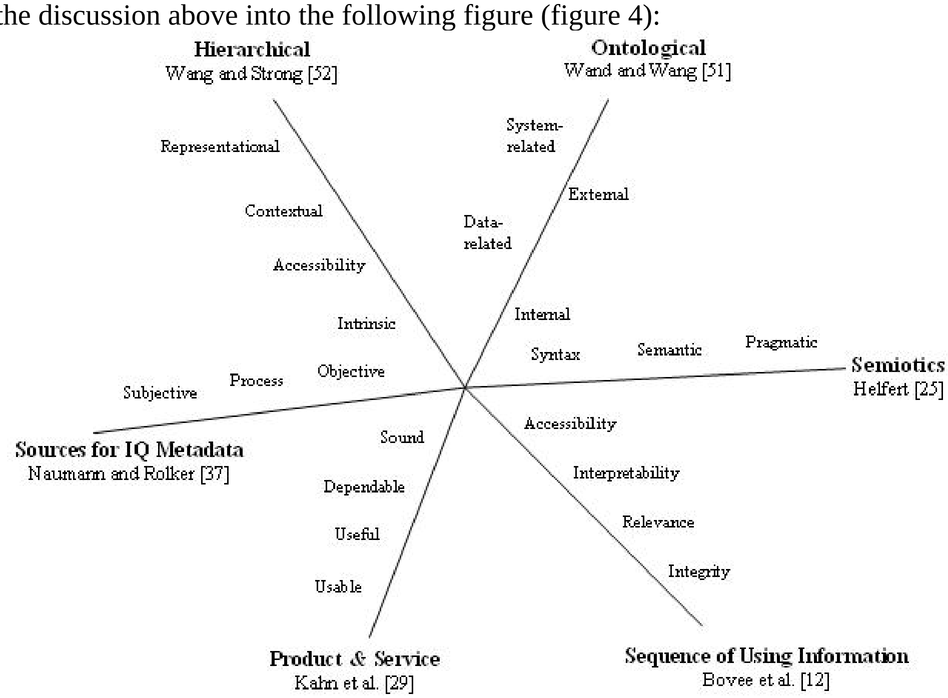


Figure 4: Classifications of IQ dimensions

Dependency of IQ Dimension

A number of literatures have analyzed dependencies of IQ dimensions. Ballou and Pazer [7] propose a framework to investigate the tradeoffs between accuracy and timeliness in the context of decision making. Redman [43] points out that time-related dimensions change can have an influence on data accuracy. Ballou and Pazer [10] model the utility of combinations of completeness and consistency in the decision context. Olson [39] implies the relationship between accuracy and completeness and states that consistency is a part of accuracy. Cappiello et al. [14] analyze the time-related accuracy and time-related completeness in multi-channel information systems. Amicis et al. [3] propose a data-driven approach to analyze the dependency of syntactic accuracy and timeliness as well as the dependency of completeness and timeliness. We structure the literatures above into the following figure (figure 5):

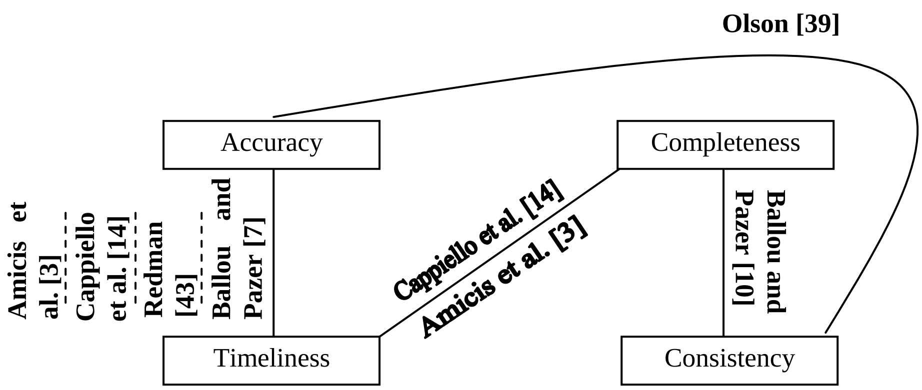
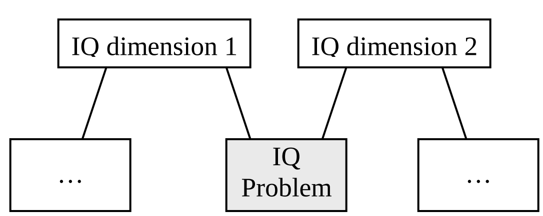


Figure 5: Dependencies of IQ dimensions

Observing the literatures above, we divide dependencies of IQ dimensions into two categories: negative correlation and positive correlation. Negative correlation refers to the improvement of one IQ dimension may lead to a decreasing goal value in another dimension. For example, by introducing new information to improve completeness, the new introduced information may be inconsistent with the existing information. In this manner, completeness and consistence are negatively correlated. For the negative correlation, we classify two kinds of tradeoffs between IQ dimensions: (1) the faster the information is delivered, the less time is available to check other IQ dimensions, and (2) when the new information is introduced to improve certain IQ dimensions, the new information may lead to a decreasing goal value in other dimensions. Positive correlation means two IQ dimensions are mutually responsible to and sharing a common set of IQ problems. For example, when timeliness and accuracy are sharing outdated data as their common IQ problem, the improvement of timeliness may lead to an increasing value in accuracy. In this way, timeliness and accuracy are positively correlated. According to the discussion above, we summarize correlations of IQ dimensions in the following table (table 2).

<table>
<tr><th>Negative Correlation</th><th>Positive Correlation</th></tr>
<tr><td>The faster the information is delivered, the less time is available to check other IQ dimensions: tradeoffs between (1) Timeliness and other IQ dimensions, (2) currency and other IQ dimensions.
When the new information is introduced to improve certain IQ dimension, the new information may lead to a decreasing goal value in other dimensions: tradeoffs between (1) completeness and other dimensions, (2) accessibility and other dimensions, (3) security and other dimensions, (4) relevancy and other dimensions.</td><td>

When we improve IQ dimension 1, IQ dimension 2 may be improved or stay at the same quality value. It depends on whether we fix the mutual IQ problem.</td></tr>
</table>

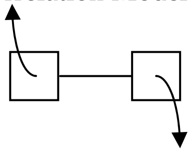
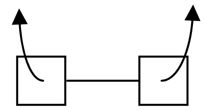
Negative Correlation Model	Positive Correlation Model
	

Table 2: Dependencies of IQ problems

IQ Assessment Methodology

A variety of IQ assessment methodologies are proposed over the last decade. We select five typical methodologies ([43], [24], [34], [42], and [49]) and evaluate them by five criteria: definitions of IQ dimensions, classifications of IQ dimensions, model, tool, and case study. Definitions of IQ dimensions focus on how many IQ dimensions are defined from which perspective. Classifications of IQ dimensions are used to compare the classification of dimensions in each methodology. Model is to demonstrate the theoretical basis of the methodologies. Tool is used to check the implementation of the methodologies. Case study concentrates on empirical feasibility of these methodologies. Using the criteria above, we can obtain the characteristics of each methodology.

IQ research is essentially divided into two communities: database and management [41]. Thus the methodology, which is only applied to one community, is considered as specific methodology. If the methodology can be applied to both communities, it is a generic methodology. If the case study is provided in the literature, we regard it as a practical study otherwise it is theoretical. We summarize the five methodologies in the following table (Table 3).

	Redman [43]	Huang et al [24]	Lee et al. [34]	Pipino et al. [42]	Stvilia et al. [49]
Definition	12 IQ dimensions are defined from the data perspective.	16 IQ dimensions are defined from the user perspective.	A dimension list consisting of 15 IQ dimensions is provided	16 IQ dimensions are defined from the data and user perspective.	22 IQ dimensions are defined from the data and user perspective
Classification	IQ dimensions are classified by value and representation	Use the classifications of Wang and Strong [52]	Use the classifications of Kahn et al. [29]	Without classifications	Adapted from classifications of Wang and Strong [52]
Model	A step by step procedure adapted from statistical process control in manufacturing	Use the data deficiency model of Wand and Wang [52]	Use the PSP/IQ model of Kahn et al. [29]	The model combines subjective and objective assessment	The model consists of activity types, IQ Problems, and taxonomy of IQ dimensions
Tool	DCI system	IQ assessment survey	IQ assessment survey	IQ assessment Software	Checklist
Case Study	Telstra Co. Ltd.	Appliance Company		1, Global Consumer Goods, Inc., (GCG) 2, Data Product Manufacturing, Inc. (DPM)	1, Simple Dublin Core (DC) 2, English Wikipedia
Conclusion	Specific, practical	Specific, practical	Generic, Theoretical	Generic, practical	Generic, practical

Table 3: Evaluation of IQ assessment methodologies

Pipino et al. [42] categorized IQ assessment into objective and subjective assessment. Objective IQ assessments reveal the IQ problems in data sets and subjective IQ assessments reflect the needs and experiences of data consumers. We follow this taxonomy and discuss IQ assessment from objective and subjective perspectives.

Objective IQ assessment is to measure the extent to which information conforms to quality specifications and references. We classify the objective IQ assessment into two categories: intrinsic and real-world IQ assessment. Intrinsic IQ assessment follows the data perspective and focuses on the quality of the data values in the database. For example, Savchenko [48] develops item frequency rules and regular expression patterns to facilitate the automated intrinsic IQ assessment. Real-world assessment follows the ontological perspective and focuses on IQ deficiencies that can take place during the system design and data production. For example, Wand and Wang [51] identify data mapping deficiencies between the real world state and information system representation. Overall objective IQ assessment can be considered as the procedure of comparing current data value with optimal data value.

Subjective IQ assessment is to measure the extent to which information is fitness for use by data consumers. These data consumers assess IQ according to their demands and expectations. Thus subjective IQ assessment follows the user perspective and focuses on discrepancy between current quality of information and user's expectation. In subjective IQ assessment, the survey is usually used as measuring instrument. Each item of the survey is evaluated by the Likert type scale in each IQ dimension. In order to indicate the differences between objective and subjective IQ assessment, we compare them by the following table (table 4):

Benchmark / Feature	Objective	Subjective
Tool	Software	Survey
Measuring Target	Datum	Representational Information
Measuring Standard	Rules, Patterns	User Satisfaction
Process	Automated	User Involved
Result	Single	Multiple
Data storage	Databases	Business Contexts

Table 4: Comparison of objective and subjective IQ assessment

Objective IQ assessment always uses software to automatically measure the datum in database by a set of quality rules whereas subjective IQ assessment always uses survey to measure the contextual information by data consumers. A single assessment result can be obtained from objective IQ assessment but we may obtain different assessment results from subjective IQ assessment. With the development of both objective and subjective IQ assessment, researchers suggested to combine these two assessment methodologies. Kahn et al [29] propose the PSP/IQ model in which they assign two views of quality: conforming to specifications (objective) and meeting or exceeding consumer expectations (subjective). Pipino et al. [42] combine objective and subjective IQ assessments and provide a framework for improving IQ. Overall we could observe a trend of combining the objective and subjective IQ assessments. However, two questions are still under research:

- How to coordinate and manage the multiple subjective assessment results?

Different data consumers highly probably generate different assessment results. For example, data custodians and managers draw completely different assessment results because some information is accessible to data custodians but inaccessible to managers.

- How to coordinate and manage the discrepancies between objective and subjective assessment results?

Objective and subjective results may be inconsistent. For example, the information may be structure complete but content incomplete. That means the information is objectively high quality and subjectively low quality.

IQ MANAGEMENT

Considering IQ assessment as a foundation for IQ management, the objective of IQ management is to improve the usefulness and validity of the information [18]. IQ management has merged three realms of management: quality management, information management and knowledge management. We express the merging trend by the following figure (figure 6):

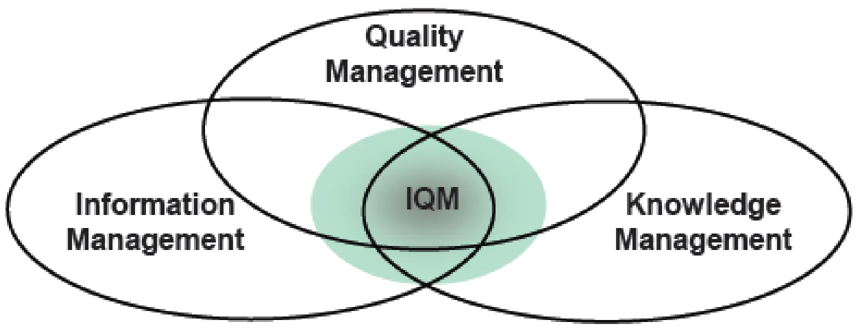


Figure 6: IQ management (IQM)

We select three typical literatures, which respectively merge quality management, information management and knowledge management into IQ management, to analyze the current research of IQ management.

- Quality Perspective: With the principle “manage your information as a product”, Wang [53] proposes a total data quality management (TDQM) methodology, which consists of four stages: define, measure, analyze and improve. The objective of TDQM is to deliver high-quality information products to information consumers.
- Information Perspective: With the principle “Integration, validation, contextualization, activation”, Eppler [18] proposes a framework, which includes four steps: identification, evaluation, allocation and application. The objective of this framework is to structure the IQ handling and value adding activities.
- Knowledge Perspective: With the principle “Know-what, know-how, know-why”, Huang et al. [24] propose a framework, which comprises three processes: improve quality of information, make tacit knowledge explicit, and create organizational knowledge. The objective of this framework is to transform high-quality information into organizational knowledge.

Based on the relationship between IQ and other research fields, the above three literatures investigate IQ management from different perspectives. Wang [53] connects IQ management and quality management by considering information as product. Eppler [18] connects IQ management and information management by employing information usage cycle. Huang et al. [24] connects IQ management and knowledge management by the relationship between information and knowledge. Regarding the development of IQ management in different perspectives, a comprehensive framework for IQ management is needed in the further research.

CONTEXTUAL IQ

Recognizing the importance of IQ, researchers have applied IQ theory to various organizational contexts. In the following table (table 5), we summarize these application contexts within last ten years (1996-2006).

Application Context	Publications
Database	Redman 1996 [43]
Information Manufacture System	Ballou et al. 1998 [8]
Accounting	Kaplan et al. 1998 [30]
Marketing	Teflian 1999 [50]
Data Warehouse	English 1999 [17]
Decision Making	Chengalur-Smith et al.1999 [15]
Healthcare	Berndt et al. 2001 [13]
Enterprise Resource Planning	Xu et al. 2002 [57]
Customer Relationship Management	Helfert and Heinrich 2003 [26]
Finance	Amicis and Batini 2004 [4]
E-business	Xu and Koronios 2004 [58]
World Wide Web	Knight and Burn 2005 [33]
Supply Chain Management	Li and Lin 2006 [36]

Table 5: IQ application contexts within last ten years (1996-2006)

Among the above application contexts, we select and analyze two most cited contexts: information system and decision making.

IQ and Information Systems

Most of the foundational IQ research is originated from information system research. Information system researchers initially identify and employ a set of dimensions to address the IQ problems in information systems. For example, Ahituv [1] uses five IQ criteria, which are accuracy, timeliness, relevance, aggregation and formatting, to assess the value of the information system. Olson and Lucas [40] evaluate information systems by using accuracy and appearance. With the increasing IQ requirements, researchers begin to focus on IQ framework [5] [56], IQ dimension [43] [52], IQ assessment [51] [17] and IQ management [53] [24]. As IQ research is developing, IQ theory is applied back to the context of information system. We select 13 most cited articles and use the following figure (figure 7) to clarify the relationship between IQ and information system:

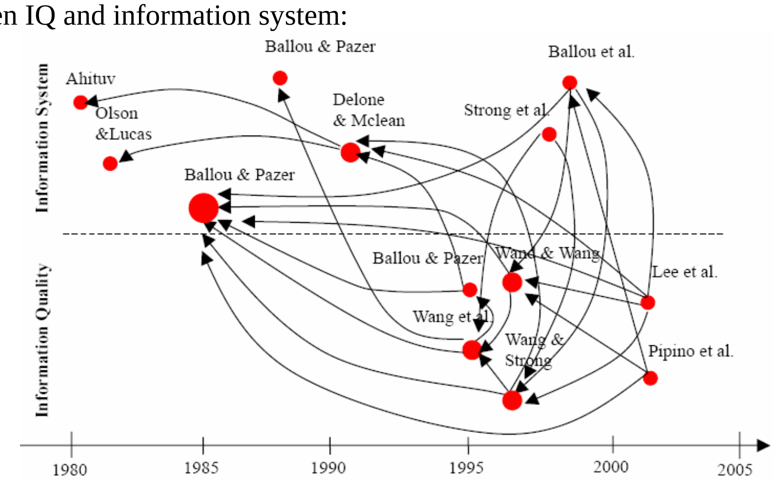


Figure 7: IQ and information system

In figure 7, the bigger the point is, the more the article is cited. Thus we can observe that the work of Ballou and Pazer [5] is cited by all the selected IQ articles. Therefore Ballou and Pazer have done a pioneering work for IQ research. Additionally, Ballou and Pazer are authors with a high impact on the study of IQ in information system research. The work of Delone and Mclean [16] reviews the information system literatures and is cited by subsequent IQ research. So Delone and Mclean have done a connection work between IQ and information system.

IQ and Decision Making

With considering other influencing factors on decision making, many researchers have shown the influence of IQ on decision making. Regarding information overload, Keller and Staelin [32] propose a model on how decision effectiveness is affected by IQ and information quantity. By employing social interaction and decision aids, Sage [46] implies that a major purpose of social interaction and decision aids is to enhance IQ, through this, to enhance the quality of decision making. Based on crisis decision environments and decision aids, Belardo and Pazer [11] propose a model to present the relationship between IQ and decision quality. In view of decision strategy and decision cost, Ballou and Pazer [7] analyze trade-off of two IQ dimension (accuracy and timeliness) in decision making. Taking task complexity and decision strategy into account, Chengalur-Smith et al [15] has shown that including the information about IQ can impact the decision making process. Considering the impact of time, expertise, task complexity and decision strategy, Fisher et al [20] develop an experiment to address the utility of IQ information in decision making. Towards dynamic decision environments, Shankaranarayan [45] propose a virtual business environment to address the role of IQ management in dynamic decision environment. From the task complexity and IQ categorization perspective, Jung and Olfman [27] find the affects of contextual IQ on decision performance were significant. From the above literatures, we could observe that various factors are considered when researchers report the impact of IQ on decision making. That means IQ could influence decision making under different decision scenarios. These decision scenarios are developed by the control of various influencing factors. We structure the above discussion into the following table (table 6):

Factor / Author	**IQ**	Information overload	Decision aids	Decision strategy	Task complexity	Expertise	Time	Environment
Keller and Staelin [32]	×	×						
Sage [46]	×		×					
Ballou and Pazer [7]	×	×						×
Belardo and Pazer [11]	×	×	×					×
Ahituv et al. [2]	×					×	×	
Chengalur-Smith et al [15]	×			×	×			
Shankaranarayan [45]	×							×
Fisher et al [20]	×			×	×	×	×	
Jung and Olfman [27]	×				×			

Table 6: IQ and decision making

From the table above, we can identify following research gaps of IQ research in decision making: (1)

Extraneous variables need to be controlled in the IQ experimental research. (2) Interaction and information presentation, which are two important factors influencing decision making, need to be investigated as independent variables in the research of IQ effects on decision making.

CONCLUSION

The review of IQ research uncovers potential research questions concerning IQ assessment, IQ management and contextual IQ. In this section, we briefly highlight the research themes to bridge the research gaps in IQ research.

We have analyzed three components of IQ assessment: IQ problems, IQ dimensions and IQ assessment methodologies. The analysis result has shown that data that is of high quality in one context may be considered to be of low quality in another context; Data that is considered to be of high quality by one person may be considered to be of low quality by another person; Data that is of high quality according to the conformity to one specification may be of low quality according to the conformity to another specification. Therefore a major research issue is still facing organizations: how to assess IQ effectively. In order to resolve this issue, subsequent issues are generated such as how to identify potential IQ problems, how to define and select IQ dimensions and how to connect IQ dimensions to IQ problems. Facing these challenges, we propose the following research issues concerning IQ assessment.

Research Issues Concerning IQ Assessment
Research Question 1: How to assess IQ effectively?
Research Question 1a: How to identify potential IQ problems?
Research Question 1b: how to define and select IQ dimensions?
Research Question 1c: What is the relationship between IQ problems and IQ dimensions?
Research Question 1d: How are IQ dimensions dependent with each other? And how to deal with the dependencies of IQ dimensions?
Research Question 1e: Which is the most suitable IQ assessment methodology for organizations?

IQ management has merged three domains of management: quality management, information management and knowledge management. With the broad view of IQ management, it is difficult to deploy IQ management in organizations. Thus in the empirical applications, organizations are still facing the issues on how to manage IQ. Following this issue, organizations need to understand the cost and benefit of IQ management, how to deploy IQ management and how to build IQ culture in organizations. Hence a comprehensive framework is needed for IQ management in the future research. We propose the following research issues concerning IQ management.

Research Issues Concerning IQ Management
Research Question 2: How to manage IQ in organizations?
Research Question 2a: How to analyze cost and benefit of IQ management?
Research Question 2b: How to evaluate the maturity of IQ management?
Research Question 2c: How to deploy IQ management in organizations?
Research Question 2d: How to build IQ awareness and IQ culture in organizations?

IQ theory has been applied to various application contexts. Following an overview of these application contexts, we select two most cited contexts: information system and decision making to analyze contextual IQ research. Because IQ research stems from information system research, understanding the relationship between IQ and information system is valuable for conducting further IQ research. Our analysis has shown the citation relationship between IQ research and information system research.

However a comprehensive analysis is still needed between the two fields. In the study of IQ in decision-making context, we have shown that considering different influencing factors researchers have shown the relationship between IQ and decision making. However the issue we are facing is how to control these influencing factors in the IQ experiment. This issue implies that controlling extraneous variables is crucial for designing IQ experiments. According to the discussion above, we summarize the issues concerning contextual IQ in the following table:

Research Issues Concerning Contextual IQ
Research Question 3: What is the relationship between IQ and application contexts?
Research Question 3a: How does IQ impact application contexts?
Research Question 3b: What is the relationship between IQ research and information system research?
Research Question 3c: How to control extraneous variables in IQ experiment?

Based on the review of IQ research, several conclusions can be drawn:

1. A solution for assessing IQ effectively is needed in organizations. Based on the review and discussion of IQ assessment, three components can be found to be important for IQ assessment: IQ problem, IQ dimension and IQ assessment methodology.

2. A comprehensive framework of IQ management is needed in organizations. Three perspective of IQ management can be found in our review. Further IQ management needs to recognize quality management, information management and knowledge management.

3. Relationships between IQ and organizational contexts need to be investigated. An overview of IQ research in contexts is provided in our work. Specifically we focus on two most cited contexts: information system and decision making. In order to facilitate IQ management, effects of IQ on application contexts need to be understood in organizations.

IQ is becoming a popular research topic and merging with other research fields. It is therefore important to be aware of necessity of IQ research in both academia and industry.

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