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THOMAS C. REDMAN*

BARRIERS TO SUCCESSFUL DATA QUALITY MANAGEMENT

Practitioners have learned that it is not the hard technical issues that stymie an organization's data quality efforts, but rather the soft, organizational, political, and social issues. For example, one such barrier is the failure to understand the enormous impact of improved data quality on business performance. Without this understanding, data quality gets short shrift. Quite naturally, practitioners have developed a variety of ways to help address these issues. Thus articulating the importance of data quality in terms of an organization's most important business (not technical) objectives helps move data quality up the priority scale.

There are many such barriers to successful data quality management and they have not been subjected to careful study. The first step is to understand what is known. Thus, in this article we briefly describe twelve common barriers, explore two especially important barriers in detail, and summarize the techniques practitioners use to address them. To conclude, we cite the disciplines that can contribute to their resolution.

Keywords: best practice, data ownership, data sharing, data standards.

* President, Navesink Consulting Group, tomredman@dataqualitysolutions.com

1. Introduction and Summary

Over the last two decades, numerous frameworks to understand data and data quality, strategies to set direction, and techniques to manage, control, and improve them have been developed (see Eppler 2003, for a summary). Organizations that have applied them consistently report stunning gains. And, as a result, costs go down, customer satisfaction goes up, decision-making improves, the risk in implementing new technologies is reduced, and so forth. So we have ample evidence that the frameworks and techniques can work, at least when consistently applied.

Given that, one must ask, "Why aren't the data good at all organizations?" The (hypothesized) short answer is that organizational, political, and social barriers impede organizations from improving data quality. [1] The way these barriers combine and interact varies from organization to organization.

To illustrate, one such barrier is that many organizations do not understand the connection between data quality and business performance. Thus quality activities get relegated to a second tier of work. Both individuals and organizations put them low on their list of priorities. And even under the best of circumstances, work on data quality gets short shrift. Worse, it is cut out altogether when time or budget grows short. Understanding and articulating the importance of data quality in terms of an organization's most important objectives, be they customer satisfaction, market share, financial performance, faster product development, or whatever, can help motivate the work more strongly, focus the effort, and move data quality up the priority scale. But not always. While some organizations seem to have an innate understanding of the importance of data quality and proceed based on that understanding, others demand, and will accept, a well-articulated business case, and still others simply refuse to believe that data quality is an issue, no matter how strong the evidence.

Unfortunately, there have been no comprehensive studies directly relevant to these barriers. This paper aims to begin to rectify this situation.

[1] Two comments. First, it is almost certainly true that organizational, political, and social barriers stymie the pursuit of any objective. Here of course, the focus is on data quality. Second, it might be helpful to clearly distinguish these three kinds of barriers from each other. But the barriers described here are themselves multi-faceted and would overlap any definitions that delineated organizational from political, from social barriers. So we don't think it will add to the discussion.

It does so by
- Summarizing these issues. The summary also clarifies the breadth and diversity of these barriers.
- Illustrating the depth of two of the most important barriers.
- Summarizing what is known about overcoming them.
- Proposing a multi-disciplinary effort for resolving them.

Both practitioners and theoreticians may view this paper as a baseline: For practitioners, even a cursory understanding of these barriers can help them advance the data quality program within their organizations. And theoreticians can use the baseline as a basis for designing more careful studies, the results of which can be used to enhance existing frameworks and techniques.

2. Twelve barriers to effective data quality management

While there have been no comprehensive studies of barriers to data quality management, there are many sources of insights, including the experiences of:
- Quality leaders in manufacturing sectors (Deming, Juran).
- Technologists who study productivity gains (Landauer).
- Reengineers (Hammer).
- Archeologists and others who have observed the roles data play in organizations (Brown and Duguid, Greene and Elfers, Strassman).
- Data quality pioneers (English, Kuan-Tsae et al., Redman).

The following is a brief description of twelve barriers to effective data quality management.[2]

1. *Poor Understanding of the Connection Between Data Quality and Performance:* Most people and organizations simply do not understand that poor quality data costs them money, angers customers, impedes decision-making, makes it more difficult to take advantage of new technologies, and so forth.

2. *Assigning Responsibility for Data Quality to the Wrong Organizations and/or People:* Perhaps the most important lesson that early data qual-

[2] Here we attempt to provide a "parsimonious" list, balancing the desires to: keep the list small, describe each issue clearly, and cover all the important barriers. Neither the list nor the descriptions are in any sense "final," as we learn more about these barriers every day.

ity practitioners learned was that you must manage data quality at sources of the data. But few organizations do so. Instead those far downstream are often left to cope as best they can. Or they assign it to a Data Quality Department. Worse, in the mistaken belief that IT can cure data quality woes (see barrier 4 below), they may assign responsibility to the IT Department. Experience confirms that these organizations can do their best to "clean-up" erred data, but that takes both time and money and the benefits are short-lived.

3. *Power/Data Sharing/Ownership:* While the issues related to power, data sharing, and data ownership are different, they are so often coupled with one another that we prefer to discuss them together. In the Industrial Age, those with bigger factories, staffs, and budgets were more powerful. The Information Age has begun to eclipse these trappings. Instead, possession of data can be a source of power. So the power hungry naturally want more control of data.

A related issue is Data Sharing. Virtually everyone praises data sharing and modern database technologies make near-universal sharing (within constraints imposed by the organization, privacy, etc.) possible, theoretically at least. But data sharing seems to be the exception, rather than the rule. Surely the pursuit of power is a contributing factor. But hoarding data has deep historical roots, as discussed further below.

Finally, the concept of "data ownership" is at best poorly defined.[3] Within an organization, people charged with improving data quality are often designated as "data owners." But they appear to have few of the rights and responsibilities usually associated with ownership. For example, an "owner" almost always has the right to sell whatever it is she owns, to whomever she pleases, at the best price she can get. But data owners clearly do not have these rights, even within the organization.

4. *Misconceptions about the Roles of Information Technologies:* Most people and organizations confuse the roles that "data" and "information technologies" can play. As an example, one often hears that "our data will be better when we implement the new system." Not only does this opinion ignore the fact that the previous system did not deliver on its

[3] It seems as though individuals should have some ownership rights to data about themselves. This topic is considered herein in Issue 12: Privacy.

promise to improve data quality, it is downright destructive. For indeed, poor data quality is often cited as one of the top reasons new systems fail (Friedman 2003).

5. *Fear of the Facts:* The age-old management dictum that "you can't manage what you don't measure" is, of course, applicable to data quality. But many people and organizations eschew measurement. They give many reasons — most are variants of "We've got a lot of smart people working very hard and using the latest technology. The data are as good as they can possibly be." A somewhat deeper look often reveals fear that measurement will reveal the true facts to managers, customers, and others.

6. *Unwillingness to reach beyond departmental/organizational boundaries:* Our working definition is that "data are of high quality if they are fit for their intended uses, by customers, in operations, decision-making, and strategy setting" (Redman 2001). In the typical organization, data created in one department are used far downstream. Much data travel from one organization to the next. And the Internet multiplies these factors.

   Given our definition of data quality, it is clear that creators and customers of data must work together to define requirements, agree on measurements, provide feedback, and conduct improvement projects. Yet this is rare. People and organizations are simply unwilling to reach up- or downstream to engage others. Many excuses are given, such as "It's their job to tell us what they want," "It's their job to know what we want," "If they don't already know what we want, then I don't see any hope of working with them," and "we can gain competitive advantage if we don't provide feedback." The result is that the lack of communications stifles any chance of improvement.

7. *Data standards have proven remarkably difficult:* Standardization has played a critical quality role in industry after industry. Though agreeing to these standards has proven difficult and implementing them even more so (Rybczynski 2000), literally millions of standards on everything from oil viscosity to the dimensions of a shipping container have become ubiquitous. Even "data communication" standards, such as XML, wind there way into common use in a relatively few years. But "data standards" have proven difficult. There are relatively

few standards and adherence to most is weak. Three exceptions are postal standards, UPC codes and the stripe on the back of a credit card.

8. *The desire to "Boil the Ocean:"* Data quality challenges come in all shapes and sizes. Many problems are readily addressed, others are unfathomably difficult. Some people and organizations have an almost pathological desire to tackle the latter. For example, some people set unrealistic goals. They may demand "100% accuracy, within six months," fully aware that the organization has ignored data quality for a generation.

   Another example involves common definitions within an organization. Many argue that their organization will be better off if all departments agree to common definitions. A common language will ease communications, reduce risk in new systems development, and improve quality. But rather than starting with something innocuous (such as "country codes"), they pick an area certain to inflame passion. Consider the term "customer." Departments use the term in subtly (and not so subtly) different ways. To Sales, a customer may be the "person who signs the contract," to Marketing, a customer may be "a prospect," to Accounts Payable, it may be "the legal entity that must pay the invoice," and to Shipping it may be "an address to which product gets shipped." Aligning these disparate definitions is no small task, especially as each department mounts a passionate defense of its "turf." This social issue and example illustrate how the issues are often intertwined. The desire to create common definitions may stem from the desire to promote standards within the organization (issue 7 above). It may also stem from a desire to streamline computer operations. The resulting common definitions will then be enforced through the organization's systems—another excellent example of an inappropriate role for IT (issue 2 above).[4]

9. *Lack of understanding about best-practice data quality management:* While the body of technique and example is growing rapidly, many people and organizations seem blissfully unaware that there are more effective and less costly ways to improve data quality.

[4] We do not wish to convey the impression that data standards, even regarding terms as slippery as "customer," are necessarily a bad idea. Just that they can be devilishly difficult.

10. The word "quality" conveys negative images: The term "quality" conjures up unsavory images in the minds of many. To many, one would only discuss "quality" when something is drastically wrong. And, they reason, those who worry about quality do not see "the big picture." It is hard to imagine these people helping the data quality effort.

11. "Management" and data flow are misaligned: Almost all organizations have a hierarchical form and feature "departments" with functional specialties such as finance, order fulfillment, product development, and so forth. So most "management" is conducted "vertically" – up and down the organization chart. But most data flow "horizontally" across the organization – from one department to the next. What began as a simple customer order, winds its way through fulfillment, inventory management, and billing. The data are aggregated with other data as part of financial reporting. Another department uses the data to understand market share. And so forth.

The point is two-fold: First, it is via the horizontal data flows that organizations create value; second, these data flows are completely unmanaged in most organizations. The situation is unacceptable.

12. Lack of Accepted Practices, Legal Frameworks, and Traditions Regarding Privacy: Much has and is being made of privacy concerns that stem from increasing abilities to share data (issue 4 notwithstanding) and analyze them in new and perhaps threatening ways. In the public sector, some argue that doing so is for the public good. It may be the best way to deter terrorism, for example. In the private sector, entrepreneurs also argue that more effective marketing is in the consumer's best interests. Different countries, companies and individuals have different perspectives on the issues. On one end of the spectrum, Scott McNealy (as quoted in Freeman, 2000) famously commented that "You have zero privacy anyway. Get over it." On the other, the legal scholar Lawrence Lessig (Lessig, 2004) views recent changes to copyright law as a grave threat to creativity. Ultimately, to data customers "privacy" may turn out to one of the most important dimensions of data quality. In the interim, it is hard to know how to proceed.

While all of these barriers merit careful description, in the next two sections we focus on two which seem to bedevil almost all organizations.

3. Barrier 1: Poor Understanding of the Connection between Data Quality and Performance

Even casual observation confirms that poor quality data are extremely damaging. Indeed, some of the most important issues of our day from trusted elections, to trusted financial statements, are rooted in poor quality (Redman 2004b). Fortunately of course, most data quality issues are not noted in the popular press. But virtually every organization is hampered by poor quality data. And the costs are indeed high. Two examples suffice. First, one study estimated the cost of poor customer data to be $611B/year in the US alone (Eckerson 2002). Second, a high fraction of new computer systems (CRM, ERP, data warehouses, etc.) fail due to inattention to data quality. According to Gartner Analyst Ted Friedman, "Through 2007, more than 50 percent of data warehouse projects will experience limited acceptance, if not outright failure, because they will not proactively address data quality issues (0.8 probability)" (Friedman 2003).

Still, many people and organizations do not make the connection between poor quality data and business performance. This failure comes in many flavors: First, some people think the data are already of very high quality. When "the computer" and "large databases" were relatively newer, we often observed that people assumed "if it's in the computer, it must be right." As the computer and databases have penetrated all aspects of society, people have become less awed by the new technology, and a new generation has grown up, we observe this phenomenon less frequently.

A large number of people are well aware that data quality is low. But they do not, on their own, connect poor quality data and the business issues they are facing. For example, they do not connect erred financial statements, the United States Presidential Election of the year 2000, or the misaddressed advertisements they receive, and data quality. Importantly, many, but not all, immediately understand the connection when it is pointed out to them.

There are a large number of people who are well aware that poor data quality is a critical issue, but don't think that anything can be done about it. They may argue that "Everyone in our business has this problem." Or they may discount the successes of others: "I know the XYZ team made huge improvements. But we're different." It can be very difficult to convince these people that order-of-magnitude improvements are possible and will yield enormous business advantage.

Finally, some individuals readily agree that improved data quality will improve business performance. But they see no strategic advantage. They argue that the first company to fully embrace data quality within their industry will incur extra costs to tailor the techniques to the specifics of the industry. They agree that the leader will incur a measure of advantage, but only for a time. The rest of the industry will "follow the leader" and catch up quickly. Indeed, these people claim, the followers will incur lower costs than the leader.

Though it is the exception, a single, committed leader, particularly a well-placed one, can start a data quality program. But more usually, a committed team (of at least several people) is needed. And more importantly, if that program is to grow, a critical mass of people must join in.[5] Further, since the impact of poor data quality is (usually) felt downstream of the source of the problem, people from different departments must engage in the effort if it is to succeed. Thus data quality must compete not only for people's hearts and minds and the organization's attention and budget, but high priority within many departments as well. And all at once.

In the extreme, a high fraction of individuals can fully recognize the importance of data quality, yet the organization as a whole will fail to take appropriate actions. This phenomenon is a specific example of the so-called Abilene Paradox (see Harvey 1996), which describes similar group dynamics in which each individual may feel that a particular course of action is misguided, but the group elects it anyway.

To conclude this section, it is important to note that there are no generally accepted methods of placing economic value on data. "Value" is usually determined in a marketplace and most data are not for sale. In contrast, there are either marketplaces or accepted accounting practices for all other organizational assets. Their absence exacerbates difficulties in connecting data quality and business performance.

4. Barrier 2: Improper Assignment of Managerial Responsibilities

As noted earlier, one of the most important dictums of practitioners is "manage data quality at the sources." And many sources contribute to even the simplest datum:

[5] The question "How many people are required to form the critical mass needed to start

- Data models, data dictionaries, and data standards are created via so-called meta-data processes.
- Data values[6] are created by business operations, including product development, manufacturing, order fulfillment, invoicing, finance, and so forth.
- Most data are stored in databases and accessed via computer applications, the result of development processes.
- Organizations create some meta-data, data values, and applications themselves. They also purchase them or otherwise obtain them from external sources. As an example, many companies purchase "credit data" and obtain "billing data" from those that provide products and services.

Table 1 summarizes these points. The implication is profound—to ensure high quality data, an organization must clearly define management accountabilities along two dimensions. A tall order, indeed.

Table 1: There are six (categories of) sources of data

	Internal	External
Meta-data	Internally developed data models, data dictionaries, business rules	Purchased data models, data dictionaries, business rules
Data values	Business processes such as order fulfillment, manufacturing, etc.; often within "applications"	Purchased data such as credit and financial data; Data obtained as part of other products/services, such as "billing data"
Access/view data	Database and application development processes	Purchased databases and applications

and/or sustain a change initiative?" is a critical one and we know of no research into the subject. I have heard claims that, for an organization of N people, the square root of N is needed if any real change is to result.

[6] As used here, a datum consists of a triple (entity, attribute, value). The first two components are (usually) defined by the data model and are created in the data modeling process. The last component is (usually) created via ongoing business processes or information chains.

Organizations can make other choices:
- They can assign responsibility for data quality to customers of the data.[7]
- They can assign responsibility to the Quality Department.
- They can assign responsibility to IT.

Customers: It is important to point out that, unless an organization makes a conscious choice, responsibility for data quality will fall to data customers. And some may argue that this is proper, since they ultimately bear the burden of poor quality. One typical example involves order fulfillment, which creates data values later summarized and used by marketing. Marketing is (usually) well advised to pore over these summaries so they are not misled by any mistakes, either in the raw data or in the summarization.

Quality Department: Some organizations have a "Data Quality Department" and charge it with "cleaning up the data." These departments are in response to business pressure, such as customer complaints, problems converting to a new computer system, or new regulations (Sarbanes-Oxley, Basel 2, etc.). Some also argue that this choice is proper—not only is the current business issue addressed, but senior management's commitment is also demonstrated.

IT: Some organizations make the IT Department responsible for data quality. There are two arguments for assigning accountability for data quality to IT. The first is usually stated something like, "If it is in the computer, it must be the province of IT." The second recognizes that IT is the source of data models (and it should be held accountable for these) so, "It will be easier to make IT responsible for all data quality issues."

Of course, none of these arguments stand up to scrutiny. The problem with these assignments, as practitioners have learned, is not that they don't conform to some theoretical model (which they don't). The problem is that the range of options is so limited, the costs are so high, the results are so poor, and that, as a practical matter, sustained improvements do not result.

[7] The usual term for those who use data and computer systems is "users." We prefer the term "customers." Some confusion may arise because the "customer" also refers to the organization's customers and customers of data may be internal. So we will use the term "data customers" to refer to those who use data to conduct operations, make decisions, set strategy, etc.

It is important to recognize that intelligent, well-meaning people make these arguments everyday. Indeed, each department may take steps that reinforce this thinking:

- A Marketing Manager may praise an analyst for "catching those errors made by those folks in Operations." The analyst sees no motivation to provide feedback to Operations. The Manager, on the other hand, is motivated to seek funding for more staff.
- The Quality Department, struggling to justify its own existence when costs are being cut, may receive credit for cleaning up a list of customer addresses. More generally, data clean-ups are big projects that give those who lead them excellent visibility.
- The IT department may recognize that poor quality data threatens the success of an important new system such as an ERP, CRM, or data warehouse. Not wishing its flagship project to fail, IT assumes responsibility for data quality.

5. Overcoming the Barriers: What is known

Data quality practitioners have been well aware that an organization's ability to get over the barriers described here, not its technological capabilities, determined the success of the data quality program. Indeed, it has long been observed that "It is the soft issues that are hard,[8]" meaning of course that it was the organizational, political, and social issues (not the technical ones) that were most difficult to solve.

Though there are subtleties, many of these issues are not so different from those faced by manufacturing quality practitioners, re-engineers, or change leaders. Figure 1 and this section briefly summarize what is known about addressing these issues. The figure uses "force-field analysis (FFA)" (Lewin 1947) to summarize the salient points. The center line represents the "level of organizational data quality." A FFA recognizes that many "forces" operate at the same time. Some, such as the issues raised in this paper, have the effect of driving quality down. These are called "restraining forces." Others act to raise the level of the data quality and are called "driving forces." At any point in time, the level represents a balance of driving and restraining forces. Further, as the figure makes clear, to raise the level, one can either add driving forces or mitigate restraining forces.

[8] We are unable to locate the source of this quote.

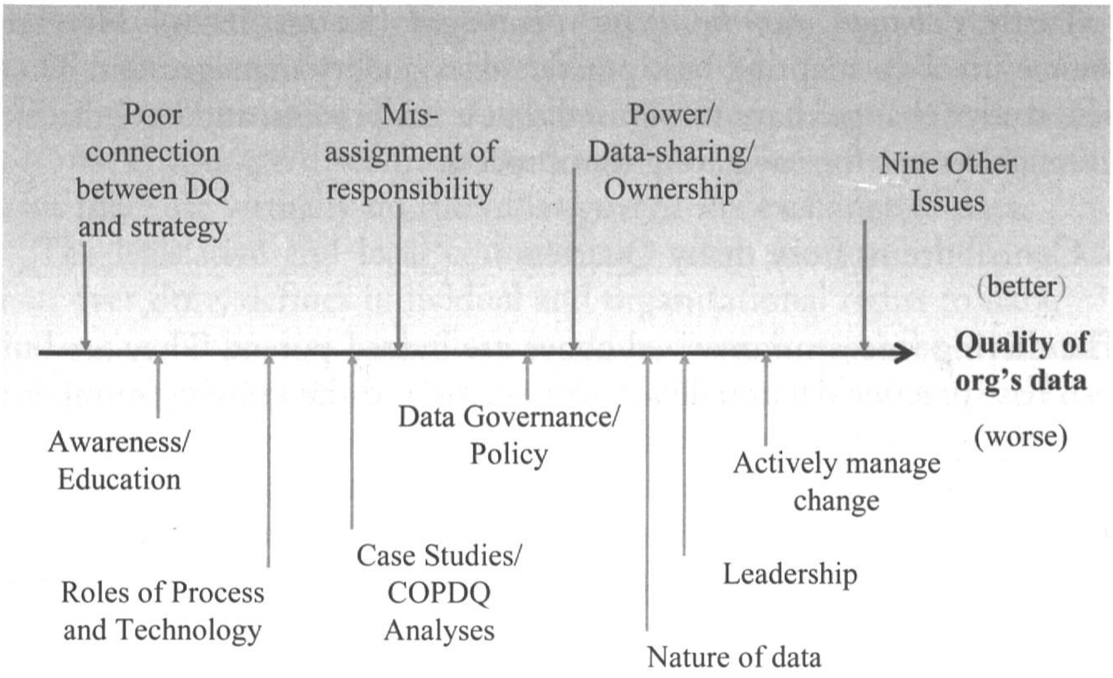

Figure 1: Force-Field Analysis: Organizational, Political and Social Barriers to Data Quality

An important first step is *awareness* of social issues and their importance. And over the long-term, there is no substitute for *education.*

Quality practitioners have long counseled that *new technologies will not improve a poorly-performing process* (Deming 1982 and Juran 1964). This counsel is proving just as apt for data as it is for manufacturing (see also Landauer 1997). One must first change the process.

Cost-of-Poor-Data-Quality analyses can make the business case for data quality more potent, and *case studies* help people learn from the successes and failures of others.

Models of *data governance* (Redman 2004 a; Strassmann 1995) recognize and help address these issues. Especially important is a *data quality policy* that properly aligns management accountabilities.

Data have many properties that are unlike any other asset. For example, one cannot *copy* financial or human resources like one can copy (much, but not all) data. Better understanding of the *nature of data* enables better management (Brown and Duguid 2000; Levitin and Redman 1998).

The issues described here make plain the need for committed senior *leadership* (see also Hammer 1996). The higher and broader the better.

Lastly, *"change" can be actively managed* (Kotter 1996). Here the change involves adapting best-practice data quality management. Those who study "change" have recognized that it is a process, and have distilled actionable steps for navigating that process.

6. Contributions from many Quarters

The driving forces summarized above are indeed potent. They are built into best-practice data quality management and the growing number of data quality successes bears testament that "they work." Still, even casual observation confirms that high-quality data are the exception. Evidently the organizational, political, and social issues are even more potent, right now anyway. Better ways to understand and address the issues are needed and can come from many disciplines. Here we suggest several.

First, many groups can help develop more compelling business cases. Accountants can develop techniques that make it easier to assemble the true "hard"[9] costs of finding and fixing erred data, responding to downstream complaints, re-running applications, failed computer systems, and so forth. Decision scientists can carefully study the impact of bad data on decision-makers and their decisions. Finally, more case studies, from all industries and government agencies, can help people more clearly see the relevance of data quality to their particular circumstances.

Organizational behaviorists can develop better ways to accommodate the cross-departmental flow of data within current (functional, hierarchical) structures or to develop new structures, perhaps based on the organization's most important business processes. They can help clarify what "data ownership" means or, better still, develop a more meaningful and useful concept.

Strategists can contribute by clarifying how "being first in the industry" to achieve and exploit superior quality data can lead to sustained advantage. Of course, not all organizations can or even should be first when it comes to data quality, just as they can not when it comes to technology, innovation, customer service, or anything else. So business strategists can help craft a range of data quality strategies, based on each organization's position within its industry and its unique skills.

Ontologists, semanticists, and others who study "meaning" may be able to devise processes for developing and implementing standards (see McComb 2004).

Political scientists, sociologists, and anthropologists can develop deeper understandings of the relationships between data and power, the nature of communities where data sharing is more common, and the factors that encourage/discourage the flow of data. Today, in most organizations there are virtually no rules that govern the exchange of data.

The legislative and legal communities must develop a body of law that, over time, defines individual and organizational rights to data.

Another important contribution must come from those who study and define marketplaces. A well-defined "internal data marketplace," within the organization, in which "sellers" sell, license, auction, or barter their data and "buyers" obtain what they need under the best terms, could both stimulate data sharing and make it easier to place economic value on data (see McMillan 2002, for a discussion of the structure of various marketplaces).

7. Final Remarks

This paper has aimed to draw attention to softer issues that hinder data quality efforts. The primary focus has been to describe twelve organizational, political, and social barriers, two in detail. A secondary focus has been to summarize what is known and suggest a path for more fully understanding and addressing these barriers.

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