

#### Peter Aiken, Ph.D.

- · I've been doing this a long time
- My work is recognized as useful
- Associate Professor of IS (vcu.edu)
- Institute for Defense Analyses (ida.org)
- DAMA International (dama.org)
- MIT CDO Society (iscdo.org)
- Anything Awesome (anythingawesome.com)
- Experienced w/ 500+ data management practices worldwide
- Multi-year immersions
  - US DoD (DISA/Army/Marines/DLA)

LITERACY

- Nokia
- Deutsche Bank
- Wells Fargo
- Walmart ...
- 12 books and dozens of articles









**Mike Frasca** Field CTO

## Data silos and complexity accelerate data quality challenges



Highly fragmented

Poor quality, duplicate data

Delays in activating data

## Reltio delivers unified, trusted core data in real-time



Single source of reliable core data

Trusted data with milliseconds latency

Time to value <90 days

Simple, flexible MDM saves costs

3

## Reltio Connected Data Platform



**RELTIO** 

## Our vision: the end to end Data Quality Lifecycle

Harness real-time data quality insights to drive upstream and downstream business impact

#### Assess

Prior to onboarding data into Reltio platform

- Understand the DQ gaps in your source data
- Compare to industry benchmarks
- Receive recommendations on how to improve DQ

#### Manage

A unified platform for measuring and managing real-time DQ

- Identify bad data & anomalies
- Reduce manual effort
- Increase effectiveness

#### Enrich

As Data is flowing through Reltio

- Recommendations for enrichment
- Pre-integrated providers for enrichment
- Measurement of ROI post enrichment

## Our vision: Reltio Real-Time Data Quality

Harness real-time data quality insights to drive upstream and downstream business impact

#### **Real-Time, Integrated**

Around the clock monitoring with a fully integrated platform

- Real time performance
- Rapid issue detection
- One-click remediation

#### **Industry Benchmarks**

Unparalleled industry specific insights

- Monitor global trends
- Define better key
   performance indicators
- Increase effectiveness

#### Recommendations

Make informed decisions effortlessly with AI

- Identify bad data
- Detect anomalies
- Reduce manual effort





## Schneider Electric uncovered several million dollars in new sales opportunities Realized cost savings, sales opportunities, and more effective service operations

#### **BUSINESS CHALLENGES**

- Wanted to improve customer experiences and speed resolution of customer issues
- Need to streamline sales and service processes
- Maintaining home-grown MDM solution was unsustainable for one person

#### SOLUTION

- Unified data across 20 systems comprised of 5M organizations and 13M individuals
- Enriched customer data with integration to Dun & Bradstreet
- Reltio Connected Data Platform as the authoritative source

#### OUTCOMES

- Several millions of new potential sales opportunities uncovered
- Saves hundreds of thousands in shipping costs per year
- 50% less time to create a new account in operational systems
- Increased efficiency for service and support teams with significantly reduced manual data entry





## Getting Data Quality Right

- Approaching Data Quality
- Cloud considerations
- Data quality attributes
- Structural versus practice-related challenges
- Digitization depends on quality data
- Definitions
- Must be built on leverage
- Data quality examples
- Causes can be difficult to discern
- High quality data requires architecture/ engineering



- What do we need to get better at?
  - Systems thinking
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  - Developing repeatable capabilities/core data quality expertise
  - PDCA
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  - Investment characteristics
  - Conversations
  - Leadership
  - Programatic focus
  - Team development
  - Tangible ROI
- Takeaways and Q&A

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#### Famous 1990's Words?

- Question:
  - Why haven't organizations taken a more proactive approach to data quality?
- Answer:
  - Fixing data quality problems is not easy
  - It is dangerous -- they'll come after you
  - Your efforts are likely to be misunderstood
  - You could make things worse
  - Now you get to fix it
- A single data quality issue can grow into a significant, unexpected investment









#### Fixing Data in the Cloud Is Like Using a Glovebox











#### New York Turns to Data To Solve Big Tree Problem

- NYC
  - 2,500,000 trees
- 11-months from 2009 to 2010
  - 4 people were killed or seriously injured by falling tree limbs in Central Park alone
- Belief



- Arborists believe that pruning and otherwise maintaining trees can keep them healthier and make them more likely to withstand a storm, decreasing the likelihood of property damage, injuries and deaths
- Until recently
  - No research or data to back it up



http://www.computerworld.com/s/article/9239793/New\_York\_Turns\_to\_Big\_Data\_to\_Solve\_Big\_Tree\_Problem?source=CTWNLE\_nlt\_datamgmt\_2013-06-05

#### **NYC's Big Tree Problem**

- Question
  - Does pruning trees in one year reduce the number of hazardous tree conditions in the following year?
- Lots of data but granularity challenges
  - Pruning data recorded block by block
  - Cleanup data recorded at the address level
  - Trees have no unique identifiers
- After downloading, cleaning, merging, analyzing and intensive modeling
  - Pruning trees for certain types of hazards caused a 22 percent reduction in the number of times the department had to send a crew for emergency cleanups
- · The best data analysis
  - Generates further questions
- NYC cannot prune each block every year
  - Building block risk profiles: number of trees, types of trees, whether the block is in a flood zone or storm zone







Digital

It isn't possible to go digital



## "I've Just Had a Recent Technology Realization" in















## The Princess on the Pea

by Hans Christian Andersen





#### Leverage Is an Engineering Concept

• Using proper engineering techniques, a human can lift a bulk that is weighs much more than the human



#### Data Quality Is a Wholistic Approach to Obtaining Data Leverage



#### Data Leverage Is a Multi-Use Concept

- Permits organizations to better manage their data
  - Within the organization, and
  - With organizational data exchange partners
  - In support of the organizational mission
- Leverage
  - Obtained by implementation of data-centric technologies, processes, and human skill sets
  - Focus on the non-ROT data
    - The bigger the organization, the greater potential leverage exists
- Treating data more asset-like simultaneously
  - Lowers organizational IT costs and
  - Increases organizational knowledge worker productivity







#### **Events Are Not Always Recognized as Data Quality Challenges?**



- IRS-coronavirus payments
- A letter from a bank
- A very expensive, very small data rounding error
- Health data story
- The chocolate story
- Covid-19





#### **IEEE** Senior Member Status (30+ Years Membership)





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#### The Seattle Times

#### **Port of Seattle**

Wednesday, August 5, 2009 - Page updated at 12:00 AM

Permission to reprint or copy this article or photo, other than personal use, must be obtained from The Seattle Times. Call 206-464-3113 or e-mail resale@seattletimes.com with your request.

#### Small construction mistake at Port of Seattle may cost \$1 million

By Bob Young Seattle Times staff reporter

A small mistake at the Port of Seattle is going to cost a lot, perhaps about \$1 million.

- Needed trench for electrical cable 2.52" - delivered 2.5"
- \$1M required to rent other facilities while new cable is obtained
- · Either rounding or truncation could explain
  - We need to get a summary on all of this," he said.
     "How did the mistake occur? Who's at fault? What are the damages? And how is money going to be recovered?"



DANIEL HOUGHTON / THE SEATTLE TIMES Tenant SSA Marine took occupancy Monday at Terminal 30, two months later than planned because a trench was built too narrow for the cranes' electrical cable.





#### Why Britain has 17,000 pregnant men

Share: 📔 More >



Comments Why Britain has 17,000 pregnant men

Posted by Sarah Kliff at 02:00 PM ET, 04/07/2012

🕞 🕘 Text Bize 🔓 Print 🖂 E-mail 📑 Reprints



(Waltred Orubitsch - AFP/Oetty Images)

The data seemed, at first glance, like it could be indicative of a medical miracle. Between 2009 and 2010, thousands of British men turned up at hospitals to be treated for many pregnancy-related services, things like obstetric exams and midwife services. All told, there were 17,000 of them. This research, published as a letter this week in the British Medical Journal, was meant to draw attention to how much data gets entered incorrectly in the country's medical system. These guys weren't turning up at the doctor for pregnancyrelated services. Instead, they were at their doctor for procedures that had medical codes similar to those of midwifery and obstetric services. With a misplaced keystroke here or there, an annual physical could become a consultation with a midwife.



### Why Using Microsoft's Tool Caused Covid-19 Results To Be Lost

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## Excel: Why using Microsoft's tool caused Covid-19 results to be lost

By Leo Kelion Technology desk editor

🛈 5 October

https://www.bbc.com/news/technology-54423988?es\_p=12801491

#### Why Using Microsoft's Tool Caused Covid-19 Results To Be Lost

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BBC O NEWS

Excel: Why using Microsoft's tool caused Covid-19 results to be lost

By Leo Kelion Technology desk editor
© 5 October



 Additional data was dropped without notification **Under-reported figures** 

From 25 Sept to 2 Oct

50,786

Cases initially reported by PHE

**15,841** Unreported cases, missed due to IT error

8 days of incomplete data 1,980 cases per day, on average, were missed in that time

**48 hours** Ideal time limit for tracing contacts after positive test

https://www.bbc.com/news/technology-54423988?es\_p=12801491

Source: PHE and gov.uk

#### How To Solve This Data Quality Problem Using Just Tools?





#### **Data Knowledge Is Too Little and Too Informal**

- Data management happens 'pretty well' at the workgroup level
  - Defining characteristic of a workgroup
  - Without guidance (strategy), what are the chances that all workgroups are pulling toward the same objectives?
  - Consider the time spent attempting informal practices
- Data chaff becomes sand in the machinery
  - Preventing smooth interoperation and exchanges
  - Losses due to lots of little data cuts have been difficult to account for
- Organizations and individuals lack data quality
  - Knowledge
  - Skills
  - Data Engineering (How?)
  - Data Strategy (Why this as opposed to that?)



Wally Easton Playing Piano https://www.youtube.com/watch?v=NNbPxSvII-Q



Data is not the new oil (its value is not based on scarcity)

Data increases in value the more it is connected





#### Everyone Wants To Do Better Data Analysis ...

- Some data preparation is inevitable
  - What would a 'good' ratio be?
  - "Everyone knows"







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#### **Burning Bridge**

- Something bad happened
  - Imperfect data was to blame
- Someone needs to fix
  - Poor quality data
- You currently have management's attention
  - It is wise to ensure you also have their understanding
- "Do something" often leads to "Buy something"
  - Mostly technology-based
- Get data quality-ing!
  - A fool with a tool is still a fool
- Something is accomplished
  - Most often all the project funding is used up



- Early cases have a dual purpose
  - Make the case that this will fix the immediate challenge
  - Illustrate why a programmatic approach is preferable



#### **Simple Math**

#### If X is invested in Y then outcome Z will result (Z > X)

- At the beginning of a project,
- · Where the parties know the least about each other
- All are expected to agree on the meaning of price, timing, and functionalities
- Define X (some resources)
- Define Y (cleaning 1 set of data)
- Define Z (that data will be clean)



#### + TRING =

#### **Simple Math**

#### If \$100 is invested in cleaning 1 set of data then outcome \$1000 will result

- Define X (\$100)
- Define Y (cleaning 1 set of data)
- Define Z (\$1000)







#### **Differences Between Programs and Projects**

- Programs are Ongoing, Projects End
  - Managing a program involves long term strategic planning and continuous process improvement is not required of a project
- Programs are Tied to the Financial Calendar
  - Program managers are often responsible for delivering results tied to the organization's financial calendar
- Program Management is Governance Intensive
  - Programs are governed by a senior board that provides direction, oversight, and control while projects tend to be less governance-intensive
- Programs Have Greater Scope of Financial Management
  - Projects typiq managemen managemen
- Program Ch Capability
- at least as long as your HR prog Projects employ a formar change level, change management requires executive leadersm change is driven more by an organization's strategy and is subject to market conditions and changing business goals



Your data quality program must |

ight forward budget and project financial

m planning,

#### **Data Quality Is Not a Project**

- Durable asset
  - An asset that has a usable life more than one year
- Reasonable project deliverables
  - 90 day increments
  - Data evolution is measured in years
- Data
  - Evolves it is not created
  - Significantly more stable
- Readymade data architectural components
  - Prerequisite to agile development
- Only alternative is to create additional data siloes!
- What Does It Mean "Data Quality Program"?
- Ongoing commitment
  - Permits evolutionary improvement of the approach
- Governance
  - Senior level coordination, direction, and control
- Executive leadership capabilities
  - Change and risk management
- Data quality approach inherits (above)
  - Budget, strategic priorities
  - Senior level attention and improving topical facility
  - Reasonable timelines/expectations



https://blog.ducenit.com/data-quality-management







#### **Leverage Point - High Performance Automation**



#### **Leverage Point - High Performance Automation**





#### **Leverage Point - High Performance Automation**

#### This cannot happen without engineering and architecture!



#### **Leverage Point - High Performance Automation**

#### This cannot happen without data engineering and architecture!





# Data Quality Engineering





- Approaching Data Quality
  - Cloud considerations
  - Data quality attributes
  - Structural versus practice-related challenges
  - Digitization depends on quality data
  - Definitions
  - Must be built on leverage
  - Data quality examples
  - Causes can be difficult to discern
  - High quality data requires architecture/ engineering



- What do we need to get better at?
  - Systems thinking
  - Not looking at data quality in isolation
  - Developing repeatable capabilities/core data quality expertise
  - PDCA
- How do we get better?
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  - Leadership
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  - Team development
  - Tangible ROI
- Takeaways and Q&A

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#### **Systems Thinking**

- A framework that is based on the belief that the component parts of a system can best be understood in the context of relationships with other systems, rather than in isolation.
- The only way to fully understand why a problem or element occurs and persists is to understand the part in relation to the whole.

Capra, F. (1996) The web of life: a new scientific understanding of living systems (1st Anchor Books ed). New York: Anchor Books. p. 30







#### How long will these challenges take to correct?



**Data Quality** 

CRM (SalesForce)





#### Programmatic Data Quality Engineering

- 1. Allow the form of the problem to guide the form of the solution
- 2. Provide a means of decomposing the problem
- 3. Feature a variety of tools simplifying system understanding
- 4. Offer a set of strategies for evolving the design of a programmatic solution
- 5. Provide criteria for evaluating the quality of the various solutions
- 6. Facilitate development of a framework for developing organizational knowledge



#### The DQE Cycle

- Deming cycle
- "Plan-do-study-act" or "plan-do-check-act"
  - Identifying data issues that are critical to the achievement of business objectives
  - Defining business requirements for data quality
  - Identifying key data quality dimensions
  - Defining business rules critical to ensuring high quality data



https://deming.org/explore/pdsa/

#### + THING = I

#### The DQE Cycle: (1) Plan

- Plan for the assessment of the current state and identification of key metrics for measuring quality
- The data quality engineering team assesses the scope of known issues
  - Determining cost and impact
  - Evaluating alternatives for addressing them





#### The DQE Cycle: (2) Deploy

- Deploy processes for measuring and improving the quality of data:
- Data profiling
  - Institute inspections and monitors to identify data issues when they occur
  - Fix flawed processes that are the root cause of data errors or correct errors downstream
  - When it is not possible to correct errors at their source, correct them at their earliest point in the data flow





#### The DQE Cycle: (3) Monitor

- Monitor the quality of data as measured against the defined business rules
- If data quality meets defined thresholds for acceptability, the processes are in control and the level of data quality meets the business requirements
- If data quality falls below acceptability thresholds, notify data stewards so they can take action during the next stage





#### + THING =

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#### **Extended Data Life Cycle Model With Metadata Sources and Uses**





## Getting Data Quality Right Engineering Success Stories

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Getting Data Quality Right

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#### **Data Investment Evaluation**

- Remember 7-of-9 from Star Trek?
- Peter's version is 1&4
  - If you invest \$1 million in any tool/technology?
  - It requires \$4 million in people and process support





#### **Compare the Utility of Data Quality Conversation Topics**

<u>_</u>	
Engineers say:	Business wants to hear:
Clean some data	Decrease the number of undeliverable targeted marketing ads
Reorganize the database	Increase the ability of the salesforce to perform their own analyses
Develop a taxonomy	Create a common vocabulary for the organization
Optimize a query	Shaved 1 second off a task that runs a billion times a day
Reverse engineer the legacy system	Understand: what was good about the old system so it can be formally preserved and, what was bad so it can be improved



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#### **CDO Agenda**

The CDOs goal is to better manage data as an organizational asset in support of the organizational mission!

Inventory Data -> uncovering assets & decreasing ROT

AGEND



Develop the first version of an organizational data strategy

All DI HIS TEALITES HIRITIS HOLD Monetize your organization's data



#### **Initially Pick One or the Other but Not Both**



#### **Improving Data Quality During System Migration**

- Challenge
  - Millions of NSN/SKUs maintained in a catalog
  - Key and other data stored in clear text/comment fields
  - Original suggestion was manual approach to text extraction
  - Left the data structuring problem unsolved
- Solution
  - Proprietary, improvable text extraction process
  - Converted non-tabular data into tabular data
  - Saved a minimum of \$5 million
  - Literally person centuries of work



Data Catalog







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#### Munge Https://En.Wikipedia.Org/Wiki/Mung\_(Computer\_Term)

- Computer jargon
- For a series of potentially destructive or irrevocable
- · Changes to a piece of data or a file
- Vague data transformation steps that are not yet clearly defined
- Common munging operations include:



- Removing punctuation
- Removing html tags
- Data parsing
- Filtering
- Transformation

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#### **Hidden Data Factories**







#### Poor Data Quality Manifests as Multifaceted Organizational Challenges





#### **Determining Diminishing Returns**

2,000,000			Unmatched Items	lgnorable Items	ltems Matched
2,000,000	W	eek #	(% Total)	(% Total)	(% Total)
	Before After	1	31.47%	1.34%	N/A
		2	21.22%	6.97%	N/A
		3	20.66%	7.49%	N/A
		4	32.48%	11.99%	55.53%
		14	9.02%	22.62%	68.36%
		15	9.06%	22.62%	68.33%
		16	9.53%	22.62%	67.85%
		17	9.5%	22.62%	67.88%
NSN/SKU V	olume	18	7.46%	22.62%	69.92%



#### Quantifying Benefits: Original Plan





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#### Quantifying Benefits: Revised Plan

Time needed to review all NSNs once over the life of the project:			
NSNs	150,000		
Average time to review & cleanse (in minutes)	5		
Total Time (in minutes)	750,000		
Time available per resource over a one year period of time:			
Work weeks in a year	48		
Work days in a week	5		
Work hours in a day	7.5		
Work minutes in a day			
Total work minutes/year	108,000		
Person years required to cleanse each NSN once prior to migration:			
Minutes needed	750,000		
Minutes available person/year			
Total Person-Years	7		
Resource Cost to cleanse NSN's prior to migration:			
Avg salary for SME year (not including overhead)	\$60,000.00		
Projected years required to cleanse/total DLA person years saved	7		
Total cost to cleanse/Total DLA savings to cleanse NSN's:	\$420,000		







#### **Quantifying Benefits:** Social Engineering

Time needed to review all NSNs once over the life of the project:			
NSNs	2,000,000		
Average time to review & cleanse (in minutes)	5		
Total Time (in minutes)	10,000, <mark>000</mark>		
Time available per resource over a one year period of time:			
Work weeks in a year	48		
Work days in a week	5		
Work hours in a day	7.5		
Work minutes in a day	450		
Total work minutes/year			
Person years required to cleanse each NSN once prior to migration:			
Minutes needed	10,000,000		
Minutes available person/year	108,000		
Total Person-Years	92.6		
Resource Cost to cleanse NSN's prior to migration:			
Avg salary for SME year (not including overhead)	\$60,000.00		
Projected years required to cleanse/total DLA person years saved	93		
Total cost to cleanse/Total DLA savings to cleanse NSN's:	\$5.5 million		



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#### **Comprehension by others is critical!**



 If others do not understand what you do then you are perceived with a cost bias



 If others understand what you do then you can be perceived with a value bias





#### Winning Cards for data quality program success

1	The project needs to be small	Projects should not be allowed to begin unless the data requirements for the entire project are <b>verified</b>	
2	The product owner or sponsor or executor must be skilled in data	Few in IT have the requisite data skills and knowledge	
3	The process must be agile-ready	Agile is a construction technique/data requires more planning before construction	
4	The team must be highly skilled in both the data quality processes and technology	Few teams have requisite levels of data skills	
5	The organization must be highly skilled at emotional maturity	Few organizations understand data stuff	9



#### This Approach Only Works if



- We can communicate precisely and correctly amongst team members, sponsors, collaborators
- We are adept with the correct technological support
- • •



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#### **Data Value Quality**

Data	Value Quality:	Attributes & Associated Definitions
V1	Correctness/Accuracy	Data values maintained are free from fault, recording defects or damage
V2	Currency	Data values maintained are the most up-to-date and match user expectations
V3	Time Period	Data values maintained cover the time period required by the users
V4	Clarity	Data values maintained match the breadth and depth of the user request parameters
V5	Precision	Data values are maintained with the amount of precision or detail required by the user
V6	Reliability	Data values stored can be depended up on by the user understated conditions
V7	Consistency	Data values continue to be maintained in a steady, dependable manner
<b>V</b> 8	Timeliness	Data values are updated as often as the user requires
V9	Relevance	Data values stored are directly responsible to the specific user needs
V10	Completeness	Attributes of entities requiring values are not null



#### **Data Representation Quality**

Data	Data Representation Quality: Attributes and Associated Definitions				
R1	Timeliness	Data should be promptly presented to the users at the time when it is needed			
R2	Conciseness	Data presented to the users match user breadth/depth requirements without data loss.			
R3	Clarity	Data are presented in a form that is easiest for the user to understand given the request circumstances			
R4	Consistency	Data presented to the users lacks nothing with respect to the user's information requirements			
R5	Detail	Data are presented in the level of detail most appropriate for the user's need			
R6	Accessibility	Data presented to the users is free from retrieval fault, data displayed unaltered from what was stored			
R7	Order	Data are presented in a sequence fitting the user's need and their cognitive style			
R8	Flexibility	Data are able to be easily transformed between systems, formats, media to best match user needs			
R9	Portability	Data are able to be migrated from application to application without data loss			
R10	Presentation Appropriateness	Data are presented in a format facilitating user comprehension			
R11	Media	Data are presented using media most effective for user comprehension			
R12	Unambiguousness/ Interpretability	Data presented to the users requires no interpretation to comprehend the correct value			

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#### **Data Model Quality**

Data	i model Quality:	Attributes & Associated Definitions
M1	Completeness	The model is comprehensive enough to be used for a reference – containing complete enough subject areas to be of use
M2	Definition Clarity/Unambiguity	The model is developed and maintained according to generally accepted modeling principles indicating the modelers consistently and correctly applied the techniques
МЗ	Relevance	The model contents represent the facts of interest to the user
M4	Value Obtainability	The data model is structured so that users can obtain the facts they require
M5	Comprehensiveness	This quality attribute addresses the issue "Did the modelers include all of the information they desired to in the model? Is this model populated with sufficient data to be useful?"
M6	Essentialness	The model contains only those elements fundamentally required to describe the subject
M7	Attribute Granularity	The model is structured so that it manipulates the level of detail desired by the users
M8	Domain Precision	The model maintains the factual precision desired by users
M9	Naturalness	The model "fits" with the way users assimilate facts into their work processes
M10	Occurrence Identifiability	The model maintains sufficient access means to uniquely identify facts required by users
M11	Robustness	Both the model component definitions and the relationships between the entities are free from interpretation-based faults
M12	Flexibility	The model is maintained in a fashion where it is able to be useful in multiple applications



#### **Data Architecture Quality**

#### Data Architecture Quality: Attributes & Associated Definitions

A1	Architectural Completeness	The architecture is comprehensive enough to be used by any functional area of the organization wishing to utilize it
A2	Architectural Correctness	The information describing the architecture is correctly represented with the appropriate methodology. That is, the organization can use the methodology to maintain uniform data definitions throughout the organization
A3	Management Utility	The data architecture is widely used by the organization in strategic planning and systems development as an indication of its utility. In practice, architectures too often wind up as shelf ware
A4	Data Management Quality	The organization as a whole is data-driven. Data models are developed and managed from an organization-wide perspective, guided by the organizational data structure. Data are managed with distributed control from a centralized unit
A5	Data Sharing Ability	The data architecture serves as the basis for negotiating and implementing
A6	Functional Data Quality	Data are engineered in support of business functional area requirements where data elements for individual systems are derived from organizational metadata requirements and implemented using organizational systems designed to support information representation
A7	Data Operation Quality	Data quality engineering is established as a functional area actively and consistently applying data quality engineering methods to data elements
<b>A</b> 8	Evolvability	The organizational data architecture is maintained in a flexible, evolving fashion to enable the fulfillment of future user requirements
A9	Organizational Self- Awareness	Organization ability to investigate architecture use and determine the types of value that it provides to end-users. Feedback helps data architects refine the architecture to make it more useful organizationally.



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**Upcoming Events** 

Time: 19:00 UTC (2:00 PM NYC) | Presented by: Peter Aiken, PhD

Strategy is Where Data Architecture and Data Governance Collide

10 October 2023



What's in Your Data Warehouse? 14 November 2023



Data Management Best Practices 12 December 2023







**III DATAVERS** 

