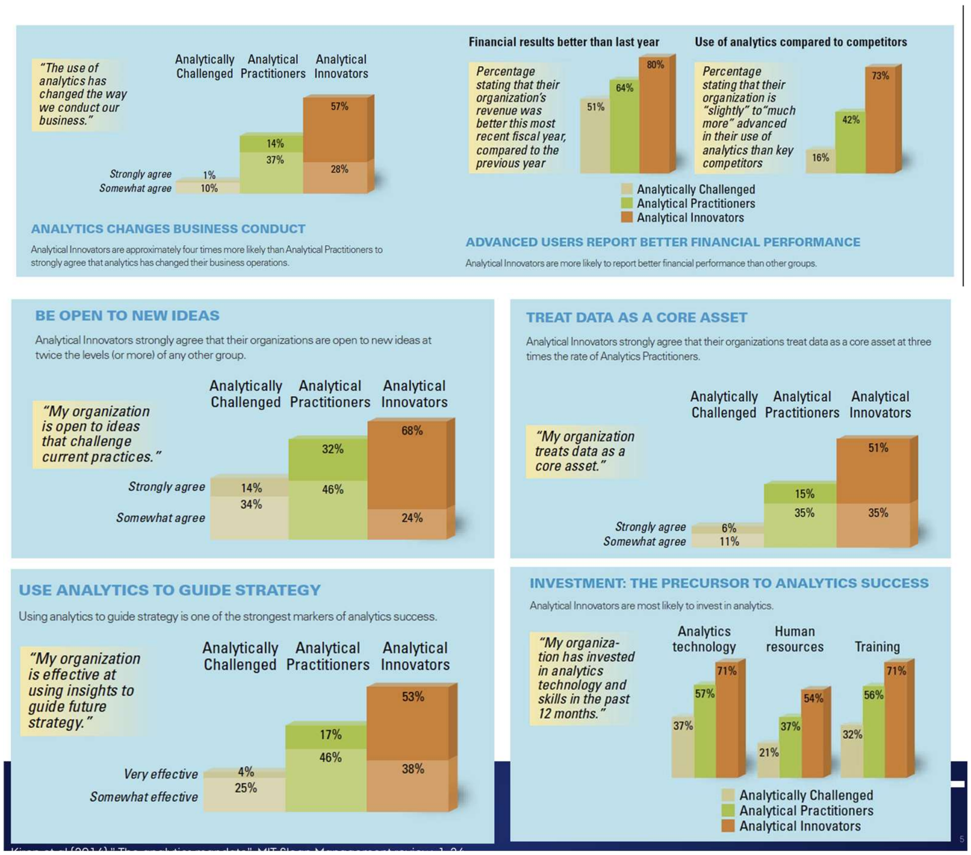
ORG BI MATURITY

Analytical Maturity

“Analytics maturity refers to an organization’s capability to use data effectively, from basic reporting to advanced, automated, and data-driven decision-making.”

- Analytics maturity = how “grown-up” a company is when it comes to using data.
- At the lowest level: they only look backwards with basic reports (like sales numbers in Excel).
- At the highest level: they use AI/automation to predict what will happen and make decisions automatically (like Amazon recommending you products in real-time

Performance



Maturity Models

Two main types of maturity models

1. Staged (or fixed-level) model
    - Think of it like a staircase:
      You must finish one whole step before you can move to the next.
    - Usually there are five generic levels (like beginner → intermediate → expert).
    - Example:
      A company must first get good at reporting before moving into predictive analytics.

   Key idea: You can't skip steps; each stage has to be "satisfactory" in all elements before progressing.

2. Continuous (or focus-area) model
    - Think of it like a spider web (different "dimensions" or "capabilities" you can improve at different speeds).
    - Instead of one staircase, you have multiple tracks (e.g., data quality, tools, culture, governance).
    - Each capability can be at a different maturity level.
    - Example:
      A company might already have strong technology (advanced tools), but weak data governance (bad data quality).

   Key idea: Capabilities can evolve separately; you don't have to be equally strong in all areas.

In practice:

- Staged models are easier to communicate (clear steps).
- Continuous models give a more realistic picture, because organizations usually don't progress evenly.

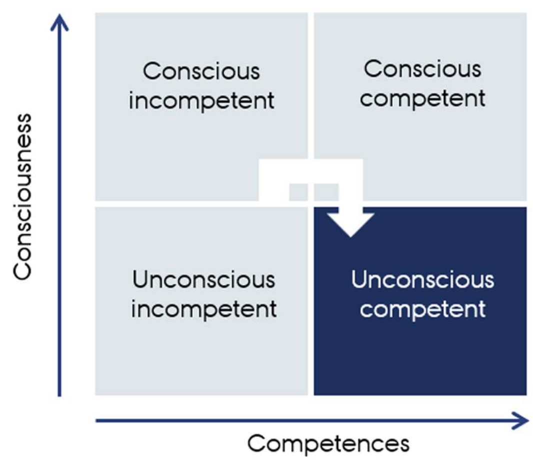
Maturity Model Use

Maturity models

Knowledge Maturity Theory

Maturity models are based on how people and organizations learn over time. Two key theories are mentioned:

1. Conscious Competence Learning Continuum (Ruona & Gilley, 2009)
    - This explains *how people gain skills*.
    - Four stages:
        1. Unconscious Incompetence → You don't know what you don't know.
        2. Conscious Incompetence → You realize what you don't know.
        3. Conscious Competence → You can do it, but you need to think about it.
        4. Unconscious Competence → You can do it naturally, without effort.



    - Example: Learning to drive a car 🚗
2. Novice-to-Expert Continuum (Benner, 1982)
    - Used in nursing and skill development, but fits BI too.
    - Stages: Novice → Advanced Beginner → Competent → Proficient → Expert.
    - Example: A beginner BI analyst makes simple Excel reports; an expert builds predictive models with ease.

Table 3.1 Information Maturity Model (IMM) Capability Definitions

INFORMATION MATURITY MODEL CAPABILITY DEFINITIONS	
Level 1 – **Aware**	No common information practices. Any pockets of information management (IM) maturity that the organization has are based on the experience and initiatives of individuals
Level 2 – **Reactive**	Little in the way of Enterprise Information Management practices. However, certain departments are aware of the importance of professionally managing information assets and have developed common practices used within their projects. At the enterprise level, a level 2 organization reacts to data quality issues as they arise
Level 3 – **Proactive**	Has a significant degree of IM maturity. Enterprise awareness, policies, procedures and standards exist and are generally utilized across all enterprise projects. At level 3, the IM practices are typically sponsored and managed by IT
Level 4 - **Managed**	Manages information as an enterprise asset. The business is heavily engaged in IM procedures and takes responsibility for the quality of information that they manage. A level 4 organization has many mature and best-in-class practices and utilizes audits to ensure compliance across all projects
Level 5 - **Optimized**	Considers information to be as much an enterprise asset as financial and material assets. A level 5 organization has best-in-class IM practices that are utilized across all enterprise projects. The distinguishing characteristic of a level 5 organization is the focus on continuous improvement. At level 5, all data management practices and assets are regularly measured and the results are analyzed as the basis for process improvement

Source: MIKE2.0 (www.openmethodology.org).

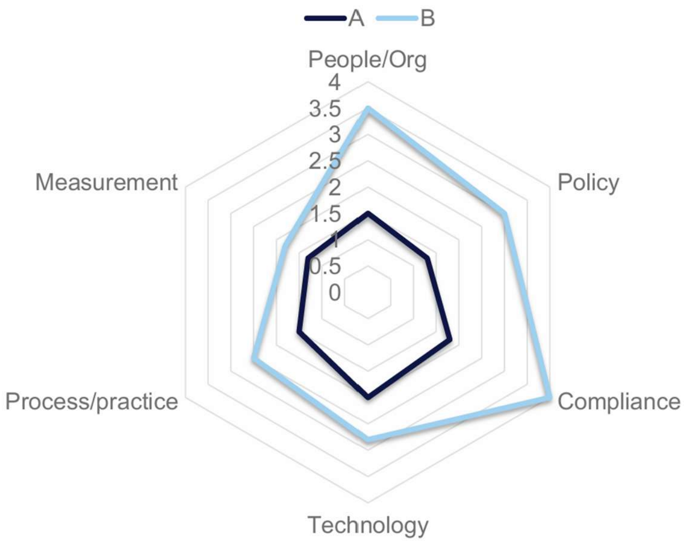
Analytics maturity

- Analytics maturity isn't just about technology. It's a combination of multiple dimensions:
    1. People / Organization → Skills, culture, leadership, how data-driven people are
    2. Measurement → How the organization measures success, KPIs, and outcomes
    3. Process / Practice → Standardized BI processes, workflows, and best practices
    4. Technology → Tools, infrastructure, software
    5. Policy → Guidelines, governance, rules
    6. Compliance → Data privacy, legal requirements, regulatory adherence
- The numbers (0 → 4) represent maturity levels:
    - 0 = Nonexistent / very basic
    - 4 = Fully mature / optimized

So, for example, a company could be:

- Tech: 3 (good tools in place)
- People: 1.5 (people not yet fully trained or data-driven)
- Process: 2 (some standard processes exist)

- Policy: 1 (policies barely defined)
- Compliance: 2 (some rules followed)



🔹 What this tells you

- Maturity is multi-dimensional → A company can be advanced in tech but weak in people/culture.
- Helps prioritize improvements → If people are lagging, investing in training and change management is key.
- Radar charts / grids like this give a quick visual snapshot of where the org stands.

Table 3. Comparison of the nomenclature of stages in the analytics continuum.

AMM	A Stage in the Analytics Continuum				
	1	2	3	4	5
1	Building reports	Building and deploying models	Building and deploying analytics	Enterprise-wide processes for analytics	Analytics is strategy driven
2	–	–	–	–	–
3	Laggard	Follower	Competitor	Leader	Innovator
4	Learning	Planning	Building	Applying	Leading
5	Analytically Impaired (Not Data Driven)	Localized Analytics (Use Reporting)	Analytical Aspirations (See the Value of Analytics)	Analytical Companies (Good at Analytics)	Analytical Competitors (Analytical Nirvana)
6	Basic	Opportunistic	Systematic	Differentiating	Transformational
7	Standalone Analytics	Bolt-On Analytics	Inline Analytics	Analytics Infused	Genius Analytics
8	–	–	–	–	–
9	Analytically Unaware	Analytically Aware	Analytically Astute	Empowered	Explorative
10	Nascent	Pre-Adoption	Early Adoption	Corporate Adoption	Mature Visionary
11	Impaired Initiated	Operational	Integrated	Competitor	Addicted

1. Analytic Processes Maturity Model (APMM). 2. Analytics Maturity Quotient Framework. 3. Blast Analytics Maturity Assessment Framework. 4. DAMM—Data Analytics Maturity Model for Associations. 5. DELTA Plus Model. 6. Gartner's Maturity Model for Data and Analytics. 7. Logi Analytics Maturity Model. 8. Online Analytics Maturity Model. 9. SAS Analytics Maturity Scorecard. 10. TDWI Analytics Maturity Model. 11. Web Analytics Maturity Model. Source: own elaboration.

BI/Analytics maturity models

1. Many models exist
    - Different frameworks exist to assess BI/Analytics maturity.
    - Despite differences, they all start from the same basic point: moving from simple reporting → advanced, data-driven decisions.
2. Focus varies by model
    - DELTAΔ → Focuses on capacity:
        - Can the organization actually use analytics effectively?
        - Measures things like leadership, culture, data quality, and change management.
    - TDWI (Transform Data With Intelligence) → Focuses on implementation status:
        - How far has the organization progressed in putting analytics into practice?
        - Measures adoption, technical infrastructure, and analytics processes.

◆ **Easy way to remember**

Model	Focus	Question it answers
DELTAΔ	Capability / readiness	"Are we ready to use analytics well?"
TDWI	Implementation / progress	"How far have we implemented analytics?"

So basically:

- DELTAΔ = *"Can we do analytics?"*
- TDWI = *"What have we actually done with analytics?"*

Item	Model	Developer
1	Analytic Processes Maturity Model (APMM)	Grossman, R.L.
2	Analytics Maturity Quotient Framework	Aryng LLC
3	Blast Analytics Maturity Assessment Framework	Blast Analytics & Marketing
4	DAMM—Data Analytics Maturity Model for Associations	Association Analytics
5	DELTA Plus Model	Davenport, T.H., Harris, J., and Morison, B.
6	Gartner's Maturity Model for Data and Analytics	Gartner, Inc.
7	Logi Analytics Maturity Model	Logi Analytics
8	Online Analytics Maturity Model	Cardinal Path
9	SAS Analytics Maturity Scorecard	SAS Institute Inc.
10	TDWI Analytics Maturity Model	TDWI, Halper, F., Stodder, D.
11	Web Analytics Maturity Model	Hamel, S.

Table 2. A comparative analysis of selected attributes of an organization's analytics maturity models (AMMs).

AMM Attributes	Analytics Maturity Models										
	1	2	3	4	5	6	7	8	9	10	11
Public availability of the methodology	■	■	■	–	■	–	■	■	–	–	■
Number of maturity levels	5	1 *	5	5	5	5	5	5	5	5	5
Number of assessment dimensions (key process areas, key elements)	6	5	6	4	7	5	1 **	6	4	5	6
Score	–	AMQ	–	–	DELTA Score	–	–	–	–	Benchmark Scores	Score

1. Analytic Processes Maturity Model (APMM). 2. Analytics Maturity Quotient Framework. 3. Blast Analytics Maturity Assessment Framework. 4. DAMM—Data Analytics Maturity Model for Associations. 5. DELTA Plus Model. 6. Gartner's Maturity Model for Data and Analytics. 7. Logi Analytics Maturity Model. 8. Online Analytics Maturity Model. 9. SAS Analytics Maturity Scorecard. 10. TDWI Analytics Maturity Model. 11. Web Analytics Maturity Model. *Overall (total) score of analytics maturity on a scale ranging from 0 to 100 points (AMQ score). ** An assessment of analytics maturity is carried out by means of surveys, in the "embedded analytics" dimension. Source: own elaboration.

Maturity Levels

1. Impaired
   - What it means: Analytics is barely used or not used at all.
   - Characteristics:
     - No centralized data
     - Decisions mostly based on gut feeling
     - Reports are ad hoc and inconsistent
2. Localized Analytics
   - What it means: Some teams use analytics, but it’s isolated.
   - Characteristics:
     - Individual departments may have dashboards or reports
     - No standardization across the organization
     - Data silos exist
3. Analytical Aspirations
   - What it means: Organization wants to be data-driven but is still developing capabilities.
   - Characteristics:
     - Some standard processes and tools
     - Leadership promoting analytics culture
     - Still gaps in skills, technology, or governance
4. Analytical Companies
   - What it means: Analytics is widely adopted and embedded in business processes.
   - Characteristics:
     - Data-driven decision-making across many functions
     - Standardized reporting and dashboards
     - Analytics used for operational and tactical decisions
5. Analytical Competitors
   - What it means: Organization is fully mature and data-driven, often gaining competitive advantage.
   - Characteristics:
     - Advanced analytics (predictive, prescriptive, AI-driven)
     - Culture, technology, and processes fully aligned
     - Analytics drives strategy and innovation

Analytic Maturity Model (DELTA)

	DATA	ENTERPRISE	LEADERSHIP	TARGETS	ANALYSTS
STAGE 5 Analytical Competitors	Relentless search for new data and metrics	All key analytical resources centrally managed	Strong leadership passion for analytical competition	Analytics support the firm's distinctive capability and strategy	World-class professional analysts and attention to analytical amateurs
STAGE 4 Analytical Companies	Integrated, accurate, common data in central warehouse	Key data, technology and analysts are centralized or networked	Leadership support for analytical competence	Analytical activity centered on a few key domains	Highly capable analysts in central or networked organization
STAGE 3 Analytical Aspirations	Organization beginning to create centralized data repository	Early stages of an enterprise-wide approach	Leaders beginning to recognize importance of analytics	Analytical efforts coalescing behind a small set of targets	Influx of analysts in key target areas
STAGE 2 Localized Analytics	Data useable, but in functional or process silos	Islands of data, technology, and expertise	Only at the function or process level	Multiple disconnected targets that may not be strategically important	Isolated pockets of analysts with no communication
STAGE 1 Analytically Impaired	Inconsistent, poor quality, poorly organized	n/a	No awareness or interest	n/a	Few skills, and these attached to specific functions

Analytical Impaired – Key Points

1. Lack prerequisites for analytics
    - The organization doesn't have the basics in place to start using analytics effectively.
    - Example: No centralized data, no BI tools, no trained staff.
2. Substantial barriers
    - There are big obstacles preventing analytics adoption.
    - Example: Siloed departments, outdated technology, or lack of budget.
3. Need to improve data quality
    - Analytics can't work well if data is messy or incomplete.
    - First step: Fix the data before trying advanced analytics.
4. The 5 Cs *(common in BI literature, often refers to core issues)*
    - While your slide doesn't define them, in analytics context they often mean:
        1. Culture – management and staff resistant to data
        2. Capability – lack of skills
        3. Change management – not ready to adapt
        4. Communication – poor reporting/insights sharing
        5. Collaboration – departments work in silos
5. Data-allergic management team
    - Leadership avoids using data, relying instead on intuition or experience.
    - Example: Proudly making gut-based decisions, not looking at numbers.

THE MATURITY LEVELS 2-4

4. **Analytical company**	Analytics is not a distinct capability Skilled, but lack out-and-out (completeness) to compete CEO support, but not passionated to compete on data
3. **Analytical aspirations**	Group value, but are in the early stages of it Competitive aspirations
2. **Localized analytics**	Pockets of analytical activity

Analytical Competitors – Key points (the best)

1. Distinct Capabilities
   - They have unique skills and systems for advanced analytics.
   - Example: Predictive models, AI algorithms, or specialized BI teams.
2. Enterprise Management Level
   - Analytics isn't just in one department; it's embedded across the whole organization.
   - Example: Marketing, sales, operations, finance all use analytics consistently.
3. Senior Management Commitment
   - Leadership actively supports and drives a data-driven culture.
   - Example: CEO and executives use analytics in every strategic decision.
4. Large-Scale Ambition
   - They aim for big, organization-wide impact with analytics.
   - Example: Using analytics to transform business models or enter new markets.
5. Aspiration to Achieve
   - They are continuously improving; it's not a static state.
   - Example: Constantly adopting new tools, techniques, and innovations.

SCANDINAVIAN EXAMPLES

Company	Davenport Stage	Why / Signals
Small/Medium Municipal Utilities (Nordic examples)	**Stage 1 – Analytically Impaired**	Often rely on spreadsheets + manual reporting, little integration of OT/IT data. Decisions made by expert judgment rather than data-driven optimization. Data governance minimal or ad hoc.
Local Retail Chains (pre-digital shift)	**Stage 2 – Localized Analytics**	Some marketing teams use basic POS reporting and loyalty card data; finance runs its own BI tool — but no shared data platform or single source of truth. Analytics remains siloed.
Regional Hospitals / Health Regions (before EHR integration projects)	**Stage 2–3 – Localized → Aspirations**	Some departments run clinical dashboards, but data not harmonized across the system; limited predictive analytics; governance improving as national health data lakes emerge.
Carlsberg (earlier digital stage)	**Stage 3 – Analytical Aspirations**	Publicly described their journey toward cloud data platform and advanced analytics as still "emerging" before 2020. Formalizing data strategy, but adoption was uneven across markets.

SCANDINAVIAN EXAMPLES

Company	Davenport Stage	Why
LEGO Group	Stage 5 – Analytical Competitor	Built a company-wide "one-stop data shop," aligned data products with business strategy, and embedded analytics into digital product development. Analytics is central to how LEGO innovates.
Maersk	Stage 4/5 – Analytical Company → Competitor	Enterprise-wide predictive analytics, real-time logistics optimization, and ecosystem data strategy. Some areas are at Stage 5 (e.g., predictive exception management), but transformation is still scaling.
Vestas	Stage 4 – Analytical Company	Strong modern data platform, IoT analytics, domain data products — but still in platform rollout phase. Becoming enterprise-wide, but not fully "competing on analytics" yet.
Danske Bank	Stage 5 – Analytical Competitor	ML models in production with measured ROI (fraud false positives down 60%, TPR up 50%), strong model governance, analytics directly impacts risk posture and profitability.
Spotify	Stage 5 – Analytical Competitor	ML-driven personalization is the product; continuous experimentation culture; analytics is a primary competitive moat.

Danish Org Maturity

Enterprises access to ICT skills (10+ employees) by activity (NACE REV2), enterprise size, topics and time

	2017	2018	2019	2020	2021	2022	2023	2024
All enterprises within the private, non-financial urban trades								
All enterprises (with at least 10 employees)								
1. Employing IT specialists	24	28	30	29	30	34	32	31
2. Offered IT upskilling to one or more types of employees	27	28	31	30	22	24	32	35
2.1 Offered IT upskilling to IT specialists	15	18	19	18	13	21	20	20
2.2 Offered IT upskilling to employees other than IT specialists	21	22	24	25	19	19	28	31
3.1 Have recruited or tried to recruit IT specialists	12	13	14	14	..	19	..	16

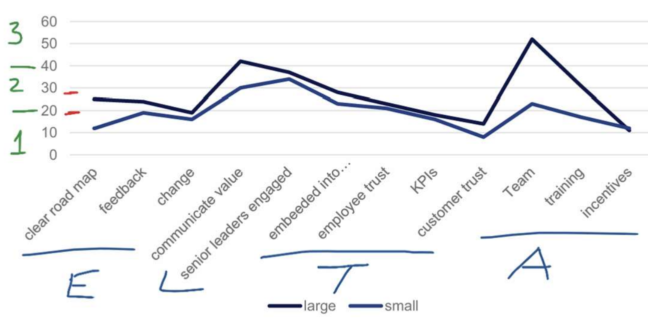
Enterprises access to ICT skills (10+ employees) by activity (NACE REV2), enterprise size, topics and time

	2017	2018	2019	2020	2021	2022	2023	2024
All enterprises within the private, non-financial urban trades								
All enterprises (with at least 10 employees)								
6.1 Own employees handled the IT functions of the enterprise	..	..	56	59	56	57	58	58
6.2 External suppliers handled the IT functions of the enterprise	..	..	75	82	78	82	82	80

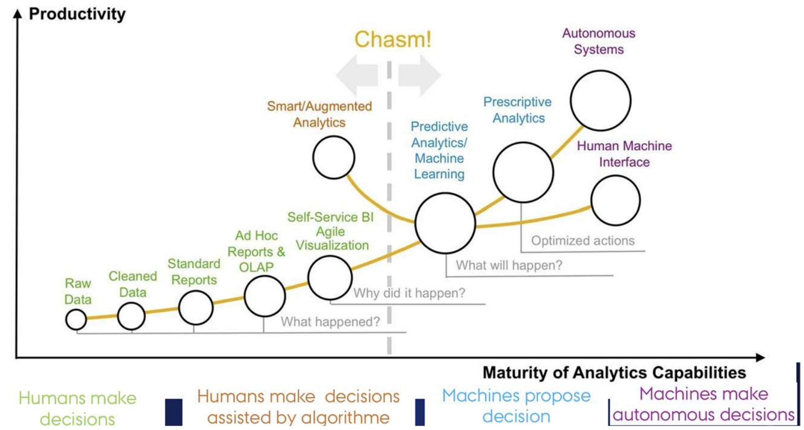
Enterprises use of cloud computing (10+ employees) by enterprise size, activity (NACE REV2), use and time

	2017	2018	2019	2020	2021	2022	2023	2024
All enterprises (with at least 10 employees)								
All enterprises within the private, non-financial urban trades								
3.1 Buying e-mail as a cloud computing service	36	41	..	56	56	..	61	..
3.2 Buying office software as a cloud computing service	27	32	..	49	47	..	55	..
3.3 Buying hosting of database(s) as a cloud computing service	28	30	..	47	47	..	51	..
3.4 Buying storage of files (except databases) as a cloud computing service	35	39	..	54	54	..	58	..
3.5 Buying accounting software applications as a cloud computing service	25	29	..	40	42	..	49	..
3.6 Buying CRM-software (Customer Relationship Management) as a cloud computing service	18	23	..	29	25	..	30	..
3.7 Buying computing power to run the enterprises own software as a cloud computing service	17	21	..	28	28	..	34	..
3.8 ERP software (Enterprise Ressource Planning)	..	..	..	..	23	..	33	..
3.9 It security systems	..	..	..	..	52	..	55	..
3.10 It-platforms for software development, test or distribution	..	..	..	..	26	..	33	..

AI ORG MATURITY – ADOPTION AND CULTURE

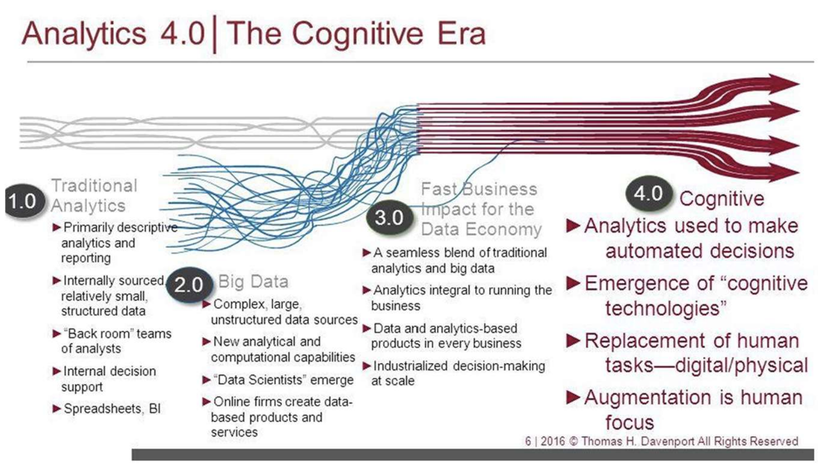


Maturity Translated Into Business Intellegience



Business Analytics

Generation	Also Called	Era / Focus	Key Idea
1.0	Traditional Analytics	The era of BI	Basic reporting and dashboards, mostly internal data, decision-making based on historical information.
2.0	Big Data	The era of internet technologies	Handling large volumes of structured & unstructured data from the web, social media, sensors. Focus on insights from massive datasets.
3.0	Data Economy	The era of connected devices / data-enriched offerings	IoT, smart devices, and real-time data. Companies create new products/services enriched with data. Example: Smart thermostats learning from usage patterns.
4.0	Agentic	The era of unlimited sources / customer-controlled data	Users/customers control and share data. Advanced analytics, AI, and autonomous decision-making. Example: Personalized recommendations or autonomous systems that act on data.



What the "eras" mean

The slide talks about four eras of analytics:

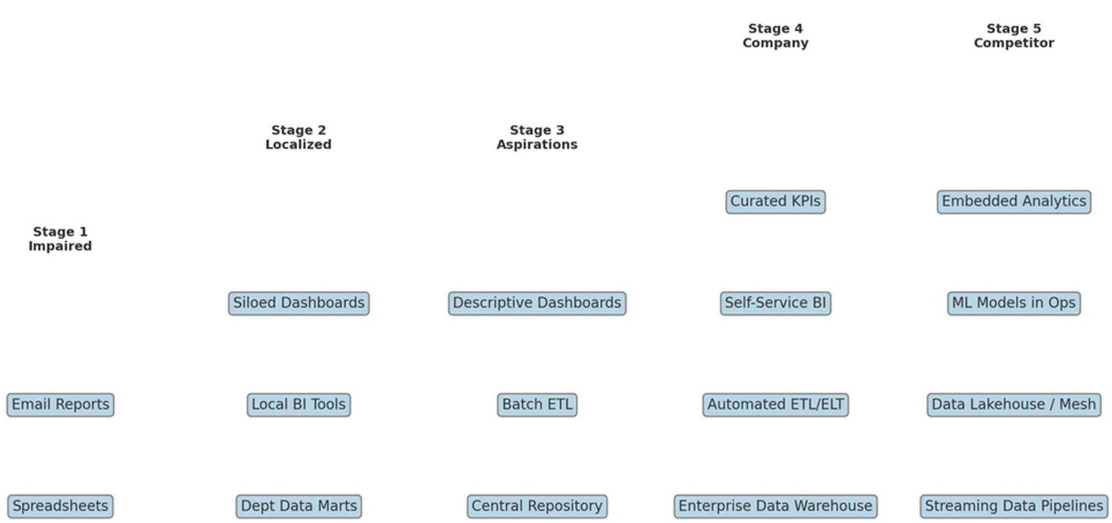
1. 1.0 Traditional Analytics → Only basic reports and dashboards.
2. 2.0 Big Data → Companies start using large amounts of internet data.
3. 3.0 Data Economy → Companies use data from connected devices (IoT) to create smarter products/services.
4. 4.0 Agentic → AI and automation, customers control some of their own data, and companies can analyze unlimited data sources.

- Important point
  - It's not about the calendar year.
    - They are stages of development, like a ladder or levels of maturity.
    - Some companies are still in 2.0, some in 3.0, and a few are moving into 4.0.

	Analytics 1.0	Analytics 2.0	Analytics 3.0
Data form	Structured	Structured and unstructured	All data
Data storage	Data bases and EDW	Cloud technologies	All
Data sources	Internal	Internal and external	All sources
Data type	Historical: retrospective	Big data	Real-time data
Analytics	Descriptive	Predictive	Prescriptive
Analytics technology	Standardize, simple reports	ML and advanced statistics	AI and advanced ML
BI tools	Traditional BI (SQL, Excel, SAP)	open source technologies like Apache Hadoop og Spark	Embedding AI; use of IoT and sensor technologies; data governance, data security; data ethics
BI organizations	IT own and control data	Decentralized analyses; data science capabilities	Decentralization and data democracy
Analytics jobs	Manual analytics	Automatic analytics	Embedded analytics
Analytics level	Basic	Starting on realtime analytics	Data is a strategic resource
Use	Reports and optimization	Customer insights, personalization, innovation	Optimizing environments and processes; automization of decision processes with AI.

Stage	BI Architecture Characteristics	Data Flow & Tools	Governance & Users
Stage 1 – Analytically Impaired	**Fragmented, manual reporting** • No formal BI system, data scattered across spreadsheets and local databases	• Ad-hoc exports from ERP/CRM • Excel, Access, CSV files • Email reports, PowerPoint summaries	• No data governance • Data owners informal, silos unconnected • Users rely on gut feel
Stage 2 – Localized Analytics	**Functional BI silos** • Each department might have its own BI/reporting tool	• Separate departmental data marts or Excel dashboards • Limited ETL, point-to-point data integrations	• Governance at function level • Analysts or "power users" emerge but rarely collaborate • Reports used mostly for hindsight
Stage 3 – Analytical Aspirations	**Centralized repository starting to form** • Early enterprise data warehouse project	• ETL processes feeding first centralized data model • Descriptive dashboards (Power BI, Tableau) become common • Batch refreshes (daily/weekly)	• Initial data governance council • IT and business start co-owning data • Executives begin asking for KPI consistency
Stage 4 – Analytical Company	**Integrated, enterprise-wide BI platform** • Single source of truth with curated data models	• Robust EDW / cloud data warehouse (Snowflake, BigQuery, Redshift) • ETL/ELT automated & monitored • Near real-time data for key domains• Self-service BI for business units	• Formal data governance & stewardship • Analytics Center of Excellence (CoE) or hub-and-spoke model • Adoption is widespread — decisions driven by dashboards
Stage 5 – Analytical Competitor	**Modern, scalable, AI-augmented architecture** • Data as a product, modular and reusable	• Real-time streaming pipelines (Kafka, Kinesis) • Advanced analytics & ML models deployed into operations • Data mesh or lakehouse approach, with domain data products • Embedded analytics in apps & workflows	• Strong governance + ethics board • Continuous monitoring of data quality & model drift • Organization-wide data literacy; business users empowered to build analyses

Evolution of BI Architecture Across Davenport's Maturity Stages



Progression Through Analytics Maturity Stages

Stage 1 → Stage 2: Analytical Impaired → Localized Analytics

- Data: Fix obvious errors, make data usable in key functions (finance, sales, ops).
- Enterprise: Allow small local initiatives ("islands of analytics") to show value.
- Leadership: Build awareness and curiosity about data at the functional level.
- Targets: Set basic, function-specific KPIs.
- Analysts: Hire or assign first functional analysts; tolerate pockets of expertise.

Stage 2 → Stage 3: Localized Analytics → Analytical Aspirations

- Data: Consolidate functional data into a central repository; standardize formats.
- Enterprise: Launch enterprise-wide data strategy, roadmap, governance.
- Leadership: Leaders recognize analytics' importance; sponsor pilot projects.
- Targets: Align analytics to small but more strategic KPIs.
- Analysts: Encourage collaboration among analysts; create informal networks.

Stage 3 → Stage 4: Analytical Aspirations → Analytical Company

- Data: Build integrated, accurate data warehouse (single source of truth).
- Enterprise: Formalize central structures (Analytics Center of Excellence, platform team).
- Leadership: Consistent support; link analytics to business strategy.
- Targets: Focus on key domains (e.g., customer churn, supply chain).
- Analysts: Embed skilled analysts in cross-functional teams.

Stage 4 → Stage 5: Analytical Company → Analytical Competitor

- Data: Expand all data sources (internal + external); use advanced analytics & ML.
- Enterprise: Centralize all key data, tech, and analyst resources; scale globally.
- Leadership: Senior management sees analytics as a competitive weapon.
- Targets: Align analytics with strategic goals and distinctive capabilities.
- Analysts: Build world-class talent; empower business users through self-service tools and data literacy programs

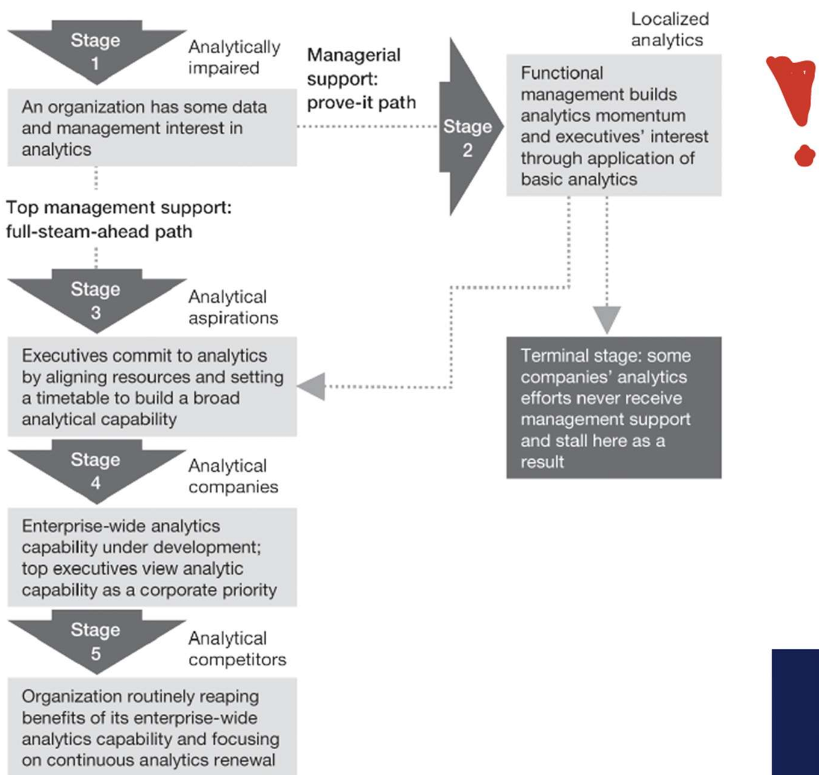
The inflection Point

Company is Between Stage 1 (Analytically Impaired) and Stage 2 (Localized Analytics).

- What's happening: Upper management is starting to realize the importance of analytics.
- External pressures push this awareness, such as:
    - Cybersecurity risks
    - Demand for transparency
    - New regulations (e.g., NIS2)
    - Need for better coordination
- Think of it as the "wake-up moment" for the organization.
- Two paths to kick-start the organizational development:
    - Full steam ahead
    - Prove-it

FIGURE 6-1

Road map to becoming an analytical competitor



Full steam ahead Path

- Requires:
    - Top management commitment
    - Strong top management commitment: CEO/executive team fully supports analytics.
    - Burning platform exists: Urgent need to compete, comply with regulations, or innovate.

    - Adequate resources: Budget, skilled people, and technology are available.
    - Change-ready culture: Employees are open to change, or resistance can be managed.
- Comes when the CEO experiences:
    - a burning platform of need to competeon analytics
    - an urgent need for change
- Challenges:
    - Entrepreneurs / startups: Need human and financial resources to implement fast.
    - Established firms: Often face heavy organizational resistance (people used to old ways).
- Key idea: Fast and ambitious, but high risk.
- Does Full Steamahead skip Stage 2?
    - No, it doesn't literally skip Stage 2 (Localized Analytics), but it moves faster through it.
    - Normally, progression is step-by-step: Stage 1 → Stage 2 → Stage 3 → ...
    - Full Steamahead is a top-down, aggressive approach:
        - Instead of slowly proving value in one function (Stage 2), the company invests heavily across multiple functions at once.
        - Stage 2 still happens, but it's compressed — you scale local analytics quickly to enterprise-level adoption.

Prove it Path

- Small wins in one team or department are used to motivate the rest of the company.
- Think of it like a spark that spreads.
- Step-by-step breakdown
    - Find an internal sponsor
        - Look for someone in the company (a manager or leader) who cares about using data and can support a project.
        - Ideally, pick a business area where analytics can clearly improve results or profit.
        - Example: Sales manager who wants better forecasting.
    - Implement smaller projects
        - Start with manageable, local projects instead of company-wide initiatives.
        - The goal is to show results quickly.
        - Example: Build a dashboard for one sales team.
    - Document before and after
        - Measure the situation before the project (baseline).
        - Measure the impact after using analytics.
        - Share the results — this creates credibility.

- Create ripples
  - Use the success story as an example to inspire other teams.
  - More departments see the value, more sponsors appear, and analytics slowly spreads.
- Key takeaway:
  - Prove-It = start small, show success, spread influence gradually.
  - Focus on practical wins that motivate others rather than trying to change the whole company at once.

Attributes of the two paths to analztical competion

Attributes of two paths to analytical competition

	Full steam ahead	Prove-it
Management sponsorship	Top general manager/CEO	Functional manager
Problem set	Strategic/distinctive capability	Local, tactical, wherever there's a sponsor
Measure/demonstrate value	Metrics of organizational performance to analytics (e.g., revenue growth, profitability, shareholder value)	Metrics of project benefits: ROI, productivity gains, cost savings
Technology	Enterprise-wide	Proliferation of analytics tools, integration challenges
People	Centralized, highly elite, skilled	Isolated pockets of excellence
Process	Embedded in process, opportunity through integration supply/demand	Stand-alone or in functional silo
Culture	Enterprise-wide, large-scale change	Departmental/functional, early adopters

Reaching Stage 3 – Analytical Aspirations

To move to Aspirations (Stage 3), a company needs:

1. Executive Sponsorship
   - Leadership actively supports analytics initiatives.
   - Example: CEO or senior manager champions a BI project and provides resources.
2. Organizational KPIs on Data
   - Business performance measures should incorporate analytics.
   - Example: Tracking customer churn, sales performance, or operational efficiency using data.
3. Process Integration
   - Analytics is embedded into business processes, not separate or ad hoc.
   - Example: Sales dashboards integrated into daily operations, not just monthly reports.
4. Analytical Architecture Supporting Data Democracy

- Systems and tools allow everyone in the organization to access and use data.
- Example: Self-service BI platforms where employees can explore data themselves.

5. At least 1 Big Organizational BI Project
    - A major project demonstrating analytics at a larger, enterprise-wide scale.
    - Example: Implementing a company-wide sales forecasting platform or customer analytics initiative.

◆ **Easy analogy**

Think of Stage 3 like **going from a local soccer team to a semi-professional team**:

Requirement	Analogy
Executive sponsorship	Coach/management fully supports and funds the team
Organizational KPIs	Set team goals and performance metrics
Process integration	Team training integrated into daily routines
Analytical architecture	Everyone can access playbooks and strategies
Big BI project	Play in a tournament to test skills on a bigger stage

Key takeaway:

- Stage 3 is about scaling and formalizing analytics, with leadership support, integrated processes, accessible data, and at least one major project proving value.

Exmples/Use Cases

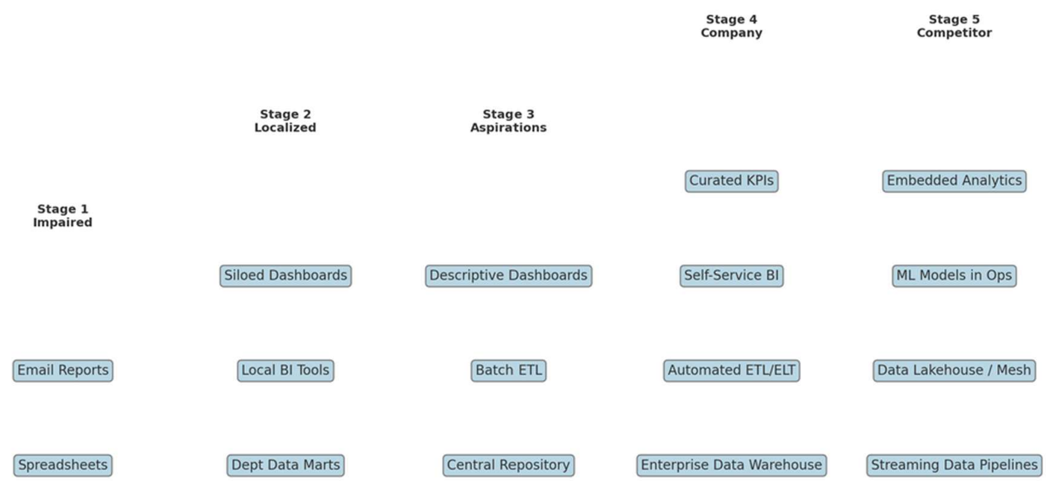
Case questions to think about

- What clues did you find in each case that signaled a high eror lower maturity level?
- Were there any "gray areas"?
- Which maturity stage did you decide for each case?
- How can the cases progress to the next stage?

What to look at:

Stage	BI Architecture Characteristics	Data Flow & Tools	Governance & Users
Stage 1 – Analytically Impaired	**Fragmented, manual reporting** • No formal BI system, data scattered across spreadsheets and local databases	• Ad-hoc exports from ERP/CRM • Excel, Access, CSV files • Email reports, PowerPoint summaries	• No data governance • Data owners informal, silos unconnected • Users rely on gut feel
Stage 2 – Localized Analytics	**Functional BI silos** • Each department might have its own BI/reporting tool	• Separate departmental data marts or Excel dashboards • Limited ETL, point-to-point data integrations	• Governance at function level • Analysts or "power users" emerge but rarely collaborate • Reports used mostly for hindsight
Stage 3 – Analytical Aspirations	**Centralized repository starting to form** • Early enterprise data warehouse project	• ETL processes feeding first centralized data model • Descriptive dashboards (Power BI, Tableau) become common • Batch refreshes (daily/weekly)	• Initial data governance council • IT and business start co-owning data • Executives begin asking for KPI consistency
Stage 4 – Analytical Company	**Integrated, enterprise-wide BI platform** • Single source of truth with curated data models	• Robust EDW / cloud data warehouse (Snowflake, BigQuery, Redshift) • ETL/ELT automated & monitored • Near real-time data for key domains• Self-service BI for business units	• Formal data governance & stewardship • Analytics Center of Excellence (CoE) or hub-and-spoke model • Adoption is widespread — decisions driven by dashboards
Stage 5 – Analytical Competitor	**Modern, scalable, AI-augmented architecture** • Data as a product, modular and reusable	• Real-time streaming pipelines (Kafka, Kinesis) • Advanced analytics & ML models deployed into operations • Data mesh or lakehouse approach, with domain data products • Embedded analytics in apps & workflows	• Strong governance + ethics board • Continuous monitoring of data quality & model drift • Organization-wide data literacy; business users empowered to build analyses

Evolution of BI Architecture Across Davenport's Maturity Stages



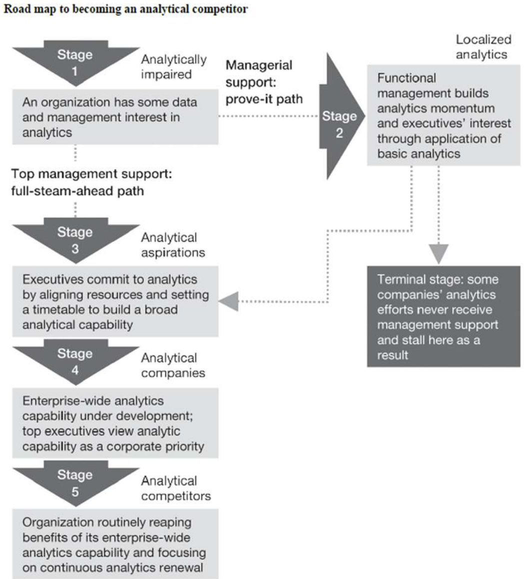
Success Factor	Stage 1 Analytically Impaired	Moving to: Stage 2 Localized Analytics	Stage 3 Analytical Aspirations	Stage 4 Analytical Companies	Stage 5 Analytical Competitors
Data	Inconsistent, poor quality, poorly organized	Data useable, but in functional or process silos	Organization beginning to create centralized data repository	Integrated, accurate, common data in central warehouse	Relentless search for new data and metrics
Enterprise	n/a	Islands of data, technology, and expertise	Early stages of an enterprise-wide approach	Key data, technology and analysts are central-ized or networked	All key analytical resources centrally managed
Leadership	No awareness or interest	Only at the function or process level	Leaders beginning to recognize importance of analytics	Leadership support for analytical competence	Strong leadership passion for analytical competition
Targets	n/a	Multiple disconnected targets that may not be strategically important	Analytical efforts coalescing behind a small set of targets	Analytical activity centered on a few key domains	Analytics support the firm's distinctive capability and strategy
Analysts	Few skills, and these attached to specific functions	Isolated pockets of analysts with no communication	Influx of analysts in key target areas	Highly capable analysts in central or networked organization	World-class professional analysts and attention to analytical amateurs

Sample Next Steps by Stage

Stage	Data	Technology	People / Organization	Process / Practice	Leadership
1 – Analytical Impaired	Fix obvious errors, make data usable	Introduce basic reporting tools	Build awareness, create curiosity about data	Start with ad hoc reports	Educate management, show value of data
2 – Localized Analytics	Standardize data formats within functions	Implement dashboards in key functions	Hire/assign first functional analysts; tolerate pockets of expertise	Produce descriptive reports, track basic KPIs	Support local initiatives, sponsor small pilots
3 – Analytical Aspirations	Consolidate functional data into central repository	Establish self-service BI tools, data warehouses	Encourage collaboration between isolated analysts	Integrate analytics into key processes; align with small strategic KPIs	Executive sponsorship; sponsor pilot projects
4 – Analytical Company	Build integrated, accurate enterprise-wide data warehouse (single source of truth)	Centralized analytics platform; enterprise BI/analytics architecture	Embed skilled analysts in cross-functional teams	Standardize dashboards and analytics processes across domains	Leadership consistently links analytics to business strategy
5 – Analytical Competitor	Expand data sources (internal + external); advanced analytics / ML	AI-driven analytics, advanced tools; scalable globally	Develop world-class analytics talent; train business users	Analytics fully integrated; drives strategic decisions	Senior management sees analytics as competitive weapon; strong commitment organization-wide

In Case it is in stage 1 decide if prove-it path or full-steam-ahead-path

Road map to becoming an analytical competitor



Case A: ScanBuild Construction

Industry: Regional construction company, 500 employees

ScanBuild recently implemented a cloud ERP and has started using Power BI dashboards for finance and project tracking. A small analytics team of two data analysts sits within Finance and produces monthly reports for management — mostly descriptive KPIs like cost overruns, project delays, and safety incidents.

Some predictive use cases are being piloted: the analysts built a model to flag projects at risk of running over budget. However, adoption is patchy: some project managers check the dashboards daily, others ignore them.

The CIO has been tasked with creating a formal data governance framework, but data quality issues remain (e.g., inconsistent project codes). The COO champions analytics and reports positive ROI from the risk model, but there's no enterprise-wide analytics center of excellence yet.

Quotes:

COO: "That risk model saved us thousands on the Bridgeport site — we caught an overrun early. But we need every PM to use it."

CIO: "We're still working on standardizing project codes. Garbage in, garbage out."

Senior Project Manager: "The dashboard is nice, but I trust my gut — I've been in construction for 20 years."

Data Analyst: "We have some great ideas for predictive models, but we can't get clean enough data for half of them."

🔹 Step 1: Current Maturity Signals

Factor	Current Status / Clues	Interpretation
Data	Data quality issues (inconsistent project codes); some predictive models pilot projects	Partially ready but messy → mid-level maturity
Technology	Cloud ERP + Power BI dashboards; dashboards mostly descriptive	Basic to moderate tech → supporting early analytics initiatives
People / Org	Small analytics team (2 analysts) in Finance; adoption patchy among PMs	Localized analytics; culture not fully data-driven
Process / Practice	Monthly reports; pilot predictive use cases; no enterprise-wide processes	Processes emerging, not standardized
Leadership	COO champions analytics; CIO working on governance; no CoE yet	Leadership support exists but limited in scale

Gray areas:

- Predictive models exist → higher maturity signal.
- Adoption is inconsistent → limits overall maturity.

Decision: Stage 3 – Analytical Aspirations

- Executive sponsorship exists.
- Predictive projects pilot-tested.
- Process and data foundation **partially in place**, but not standardized enterprise-wide.

🔹 Step 2: Practical Next Steps by Factor to Progress to Stage 4 (Analytical Company)

Factor	Next Steps
Data	- Standardize project codes and other key identifiers - Build an integrated data warehouse (single source of truth) - Improve data quality controls and validation
Technology	- Expand Power BI dashboards enterprise-wide - Introduce self-service BI tools - Plan analytics architecture to support multiple functions
People / Organization	- Embed analysts into cross-functional teams (Finance + PMs) - Hire or train additional analysts to scale capabilities - Encourage PM adoption through training and incentives
Process / Practice	- Standardize reporting processes and dashboards across projects - Align analytics with enterprise-level KPIs - Integrate predictive models into routine decision-making
Leadership	- Strengthen executive sponsorship across all functions - Create an enterprise-wide **Analytics Center of Excellence (CoE)** - Communicate ROI and value stories to encourage adoption

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🔹 Step 3: Quick Analogy

Think of ScanBuild's journey like **moving from a semi-professional sports team to a fully professional team**:

- Currently: Small, talented group in Finance (local team) with some pilot wins → **Stage 3**.
- Next: Full integration, standardized processes, cross-functional coaching, and enterprise-wide support → **Stage 4**.

Case B: NordTex Apparel

Industry: Mid-sized fashion retailer, 60 stores + online shop

NordTex uses a patchwork of Excel files and a basic point-of-sale system to track sales. Store managers manually compile weekly reports and email them to HQ, where a small finance team consolidates the numbers into a monthly PowerPoint for executives.

No data warehouse exists, and different departments (marketing, supply chain, finance) keep their own spreadsheets. Marketing decisions are based on gut feel and seasonal intuition — for example, choosing which items to promote is based on store staff's opinions, not on actual sales patterns.

There is interest from the CEO in "becoming more data-driven," but no formal data strategy, no analytics team, and no real-time dashboards.

Quotes:

CEO: "I keep hearing about 'data-driven decision-making,' but honestly, we don't even have one version of the truth when it comes to sales numbers."

Head of Marketing: "We usually go with what sold well last year — and cross our fingers."

Store Manager: "Every Monday night I'm up late sending in Excel sheets. Sometimes head office calls because my totals don't match Finance's."

Finance Analyst: "Half my job is just cleaning and merging spreadsheets."

🔹 Step 1: Identify Clues of Maturity

Factor	Current Status / Clues	Interpretation
Data	Patchwork of Excel files, no data warehouse, inconsistent numbers	Low-quality, fragmented data → Stage 1 signals
Technology	Basic POS system, manual spreadsheets, monthly PowerPoint reports	Minimal analytics technology → Stage 1
People / Organization	No analytics team; departments work in silos	Limited analytics capability → Stage 1
Process / Practice	Weekly manual reporting; decisions based on gut / seasonal intuition	Processes are ad hoc, descriptive only → Stage 1
Leadership	CEO interested but no formal strategy	Awareness exists, but no sponsorship → early Stage 1

Gray areas:

- CEO is interested in "becoming more data-driven" → signal of potential inflection point.
- But **no analytics team, no dashboards, no data strategy** → maturity still very low.

Decision: Stage 1 – Analytical Impaired

- Data is messy, technology is minimal, no formal processes or team.
- Decisions are largely gut-based.

🔹 Step 2: Practical Next Steps by Factor to Progress to Stage 2 (Localized Analytics)

Factor	Next Steps
Data	- Clean up obvious errors in Excel/ POS data - Standardize data formats (e.g., sales codes, store IDs) - Identify one key dataset to focus on first (e.g., sales by store)
Technology	- Introduce a simple BI tool or dashboard for one function (Finance or Sales) - Begin consolidating key spreadsheets into a single file or database
People / Organization	- Assign or hire a small analytics team (even 1–2 people) - Encourage collaboration between Finance and Store Managers for reporting
Process / Practice	- Start simple, repeatable reporting for one function (e.g., weekly sales report) - Document before-and-after improvements to show value
Leadership	- CEO or manager sponsors initial analytics initiatives - Communicate potential benefits of data-driven decision-making to staff

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🔹 Step 3: Analogy

Think of NordTex like **someone learning to drive for the first time**:

- Stage 1 → Sitting in the driver's seat but barely knows how to start the car.
- Next step → Learn the basics, take short trips in a controlled environment (localized reporting projects) before driving on the highway (enterprise-wide analytics).

🔹 Which Path?

Full Steam Ahead 🚂

- **Requirements:** Top management commitment, big investment, urgent need to compete.
- **Challenge for NordTex:** CEO is interested, but the company doesn't have urgency, strong analytics leadership, or resources for a huge, fast jump. Resistance might be high.

Prove-It ✅

- **How it fits NordTex:**
  - Start small (e.g., clean sales data, simple dashboards).
  - Pilot analytics in *one business area* (marketing campaigns or supply chain).
  - Show ROI → convince other departments → build momentum.
  - This matches NordTex's situation because they lack infrastructure and trust.

👉 **Best fit for Case B: Prove-It Path**

- They need bottom-up quick wins → e.g., a pilot project with clear before/after results.
- Full Steam Ahead would be too risky at this early stage.

🔹 Practical Next Step for Prove-It Path (NordTex)

- **Internal sponsor:** Pick Marketing (campaign ROI) or Supply Chain (inventory optimization).
- **Small project:** Automate weekly sales reports → show consistency vs. Excel chaos.
- **Measure ROI:** Demonstrate time saved + fewer errors.
- **Spread success:** Share results across teams to build trust and demand.
- **Then:** Build a central sales data repository → roadmap toward Stage 2.

Case C: Arctech Logistics
Industry: Global logistics and freight-forwarding

Arctech runs a modern data platform with real-time data pipelines from IoT sensors on trucks, ships, and warehouses. Machine learning models forecast demand and dynamically optimize routing and pricing.

Analytics is embedded into daily workflows: dispatchers use AI-driven dashboards, sales teams receive churn-risk scores for key accounts, and executives review live KPI boards during weekly strategy meetings.

The company has a dedicated Analytics Center of Excellence, a data literacy training program for all employees, and a clear governance policy on data ethics. Over 70% of strategic decisions are backed by data models or simulations.

Quotes:

Chief Data Officer: “Every strategic initiative starts with data — it’s our competitive edge.”

VP of Operations: “The real-time routing system cut average delivery time by 8% last quarter.”

Data Scientist: “We retrain our demand forecasting models weekly to keep accuracy above 95%.”

Dispatcher: “The dashboard tells me exactly which route will avoid tomorrow’s port congestion — I can’t imagine working without it.”

CEO: “Our customers choose us because we are the most predictable, most reliable logistics partner. That’s data at work.”

🔹 Step 1: Identify Clues of Maturity

Factor	Current Status / Clues	Interpretation
Data	Real-time IoT pipelines, retrained ML models, high accuracy forecasts	Advanced, high-quality, continuously updated data → Stage 5 signals
Technology	Modern data platform, AI-driven dashboards, simulations	Enterprise-wide, cutting-edge analytics tech → Stage 5
People / Organization	Dedicated Analytics Center of Excellence, data literacy program	Skilled, enterprise-wide analytics culture → Stage 5
Process / Practice	Analytics embedded in daily workflows, 70% of strategic decisions data-driven	Fully integrated into business processes → Stage 5
Leadership	CEO, CDO, VP fully support data-driven decisions; analytics is a **competitive edge**	Strong executive sponsorship → Stage 5

Gray areas:

- None significant — Arctech shows **consistent maturity across all factors.**

Decision: Stage 5 – Analytical Competitor

- Advanced use of analytics and ML for strategic advantage.
- Enterprise-wide adoption and strong leadership commitment.

🔹 Step 2: Practical Next Steps / Continuous Improvement

Even at Stage 5, the goal is **sustainability, innovation, and staying ahead**:

Factor	Next Steps
Data	- Explore new external data sources (e.g., market trends, weather, traffic APIs) - Continue improving ML model accuracy and retraining pipelines
Technology	- Invest in next-gen analytics tools, AI/ML frameworks, and automation - Ensure infrastructure scales globally as data volume grows
People / Organization	- Expand data literacy training - Retain and attract world-class analytics talent - Foster internal innovation competitions for analytics solutions
Process / Practice	- Continuously optimize workflows based on analytics insights - Introduce predictive scenario planning for all strategic initiatives
Leadership	- Keep promoting analytics as a **strategic weapon** - Monitor ROI of analytics initiatives and benchmark against competitors

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🔹 Step 3: Analogy

Think of Arctech like **an elite professional sports team**:

- Stage 5 → World-class players, coaches, and training facilities.
- Analytics is their **competitive edge**; data drives nearly every decision.
- Continuous improvement is essential to **stay ahead of competitors**.

Case D: PolarChem Industries

Industry: Specialty chemicals manufacturer, 4,000 employees

PolarChem invested heavily in a cloud data platform two years ago, integrating production, quality, and supply chain data into a modern data lakehouse. They hired a team of eight data scientists and five data engineers to build predictive maintenance models and optimize batch production scheduling.

Technically, the models work — predictive maintenance models achieved >90% accuracy in lab tests, and a pilot scheduling model cut downtime by 15%. However, plant managers rarely use the tools, saying they “don’t trust black-box algorithms.”

The COO is a strong analytics sponsor, but middle managers push back, preferring Excel-based planning they control. There is no formal data literacy program, and dashboards are underutilized.

Some pockets of excellence exist — one plant in Finland fully adopted the system and reports major savings — but others barely log in to the dashboards. The analytics team complains they are treated as “report builders” rather than strategic partners.

Quotes

COO: “We’ve built one of the most advanced data platforms in the industry — now we need people to use it.”

Plant Manager (Germany): “The model said to delay the batch. I’ve been doing this for 20 years — I went ahead anyway.”

Data Scientist: “We spend as much time evangelizing as we do coding. Without buy-in, our work dies in a slide deck.”

Finance Controller: “I love the live cost dashboards. I just wish more teams trusted them.”

Production Planner (Finland): “Since we started using the scheduling model, overtime costs dropped dramatically — I’d never go back.”

🔹 Step 1: Identify Maturity Signals

Factor	Current Status / Clues	Interpretation
Data & Technology	Cloud data lakehouse, predictive maintenance, scheduling models with high accuracy, live dashboards	Technically advanced (Stage 4–5 level)
People / Organization	Strong COO sponsorship, but middle managers resist. No data literacy program. Analysts treated as "report builders."	Weak adoption and cultural resistance → Stage 2–3 signals
Process / Practice	One plant (Finland) shows real impact (+15% downtime reduction, cost savings). Elsewhere, models underutilized.	Mixed adoption → Stage 3
Leadership	COO is committed, but middle management pushback = inconsistent leadership alignment	Between Stage 3 and Stage 4
Adoption	Pockets of excellence vs. broad resistance.	Indicates stuck in "Analytical Aspirations" (Stage 3)

👉 **Overall stage: Stage 2 $\boxed{3}$ – Analytical Aspirations**

- Advanced tools exist but not embedded in daily workflows.
- Adoption is uneven → the org isn't a full "Analytical Company" yet.

🔹 Step 2: Why PolarChem is stuck

- **Technology is ahead of culture.**
- Models work, but trust is missing ("black box" issue).
- Middle management resists change (fear of losing control).
- Analysts not seen as partners, but service providers.
- No systematic **data literacy** or change management program.

🔹 Step 2: Why PolarChem is stuck

- **Technology is ahead of culture.**
- Models work, but trust is missing ("black box" issue).
- Middle management resists change (fear of losing control).
- Analysts not seen as partners, but service providers.
- No systematic **data literacy** or change management program.

🔹 Step 3: Next Steps to Progress to Stage 3 ~~4~~ (Analytical Company)

Factor	Next Steps
Data & Tech	- Build model explainability (transparent dashboards, "why did the algorithm decide this?"). - Focus on *business-relevant KPIs* tied to model outcomes.
People / Org	- Launch a **data literacy program** for managers and plant staff. - Elevate analysts from "report builders" to **strategic partners** (involve them early in decisions).
Leadership	- Expand sponsorship beyond the COO → middle managers must become champions, not blockers. - Use the **success story in Finland** as proof-of-value.
Process / Practice	- Embed models into daily workflows (e.g., integrate recommendations directly into planning software). - Track adoption as a KPI ("how often are dashboards used in decisions?").
Adoption Strategy	- Follow a **"prove-it and scale" approach**: replicate Finland's success step by step in other plants. - Celebrate and communicate quick wins widely.

TEMPLATE
Business Intelligence Analysis

PURPOSE/MODEL

Davenports 5 maturity stages

Why: You need a structured framework to measure BI maturity. Davenport's model (Analytically Impaired → Localized Analytics → Analytica Aspirations → Analytical Companies → Analytical Competitors) gives a clear scale that can be applied across industries.
It helps you identify where an organization is now and what the next step looks like

UNIT organization

Why: BI maturity is not just about one function (like Finance or Marketing). True maturity needs to be assessed at the enterprise level: leadership, culture, data quality, processes, and adoption across the whole company.

Even if analysis starts locally (a pilot), the unit of maturity is the organization as a whole.

PEOPLE

Management team

Why: Leadership sets the tone for BI adoption.
If the management team trusts data, invests in governance, and sponsors projects → analytics progresses.
If management resists (gut decisions, "Excel only"), even the best tech fails.
That's why interviewing or assessing management buy-in is crucial for maturity analysis.

DATA Interview

Why: Data maturity is not only about technical integration — it's also about how people experience and trust data.
Interviews reveal:
Do managers complain about "garbage in, garbage out"?
Do different departments report conflicting numbers?
Is there a single version of the truth?
This qualitative insight complements quantitative data checks.

ANALYTICS

Assessment

Why: You need to assess the type and depth of analytic being used:
Only descriptive reports?
Some predictive pilots?
Fully prescriptive models embedded in workflows?
Assessment provides a "snapshot" of where the org stands today.

OUTPUT

Maturity stage

Why: The main output of your analysis is a classification:
Stage 1 → Imparied
Stage 2 → Localized
Stage 3 → Aspirations
Stage 4 → Analytical Company
Stage 5 → Analytical Competitor
This makes the results concrete and actionable.

APPLICATION

Orgmaturitystage Steps to progression

Why: Knowing the maturity stage only matters if it drives action.
The application is:
Show the company where they stand.
Provide specific steps to progress (e.g., data quality fixes, governance, literacy training, embedding analytics).
This bridges analysis → strategy → execution.